

Review

Review of Deterministic and AI-Based Methods for Fluid Motion Modelling and Sloshing Analysis

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Abstract: Contemporary fluid motion modelling techniques, including the phenomenon of liquid sloshing in tanks, are increasingly associated with the use of artificial intelligence methods. In addition to the still frequently used traditional analysis methods and techniques, such as FEM, CFD, VOF and FSI, there is an increasing number of publications that use elements of artificial intelligence. Among others, artificial neural networks and deep learning techniques are used here in the field of prediction and approximation, as well as genetic and other multi-agent algorithms for optimization. This article analyses the current state of research using the above techniques and the possibilities and main directions of their further development.

Keywords: liquid sloshing; modelling; artificial intelligence; neural networks; deep learning

1. Introduction

The study of fluid motion and energy modelling has garnered significant attention due to its critical role in various engineering applications. Liquid sloshing, a complex phenomenon involving the movement of free surfaces within partially filled tanks, is particularly pertinent in industries such as automotive, aerospace, marine, and energy. Understanding and mitigating the effects of sloshing are crucial for ensuring structural integrity, operational safety, and efficiency. Over the years, traditional modelling techniques like computational fluid dynamics (CFD), finite element methods (FEM, FVM), and smoothed particle hydrodynamics (SPH) have enabled significant progress in understanding fluid dynamics. These approaches provide detailed insights into the interaction between fluids and their containers, such as tanks or dampers. However, they often require substantial computational resources and are limited in addressing real-time or highly non-linear scenarios, especially under varying environmental and operational conditions. In this context, artificial intelligence (AI) has emerged as a groundbreaking tool for addressing the complexities of fluid motion modelling. AI techniques such as artificial neural networks (ANNs), genetic algorithms (GAs), and machine learning models have demonstrated remarkable potential for predictive analytics, system optimization, and real-time control. By leveraging large datasets and computational advancements, these methods provide innovative solutions to mitigate the limitations of traditional approaches, offering faster, more adaptable, and more efficient modelling capabilities. Despite these advantages, the application of AI in this field is still in its early stages, with substantial room for exploration and development.

This review emphasizes the growing relevance of AI in fluid motion energy modelling, highlighting its potential to enhance traditional methods and enable new insights. In particular, integrating AI with experimental and numerical approaches opens possibilities for



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optimizing anti-sloshing devices, improving energy dissipation strategies, and designing robust fluid systems. While advancements have been significant, the relatively few studies on the use of AI in this domain underline the necessity for further research. This makes the topic not only timely but also of great importance for future engineering innovations. Through an analysis of contemporary studies, this work aims to present a comprehensive overview of fluid motion energy modelling methods, mainly focusing on AI applications. By identifying current challenges and proposing directions for future research, this review contributes to the broader effort of advancing energy-efficient and safe designs in systems influenced by fluid dynamics.

2. Materials and Methods

Based on the initial analysis of scientific publication databases, it was decided to base the search mainly on publications indexed in Scopus and Web of Science, as well as to use the ScienceDirect search engine. A preliminary verification of the topics of articles on modelling the liquid sloshing phenomenon was performed, distinguishing three main areas: traditional deterministic methods, mainly CFD-based; neural network techniques, including machine learning; and deep learning algorithms and genetic algorithms. Additionally, it was assumed that the queries would not include articles on aerodynamics (mainly wind turbines) or thermodynamics. Since genetic algorithms are often used jointly with other technologies, the adequate query did not exclude responses containing such multidisciplinary applications. Thus, the following query strings were formulated:

- liquid tank sloshing modelling – “wind turbine” – aerospace – thermodynamic – neural – GA – genetic – neural – “deep learning” – “machine learning”,
- liquid tank sloshing modelling + neural + “deep learning” + “machine learning” – GA – genetic,
- liquid tank sloshing modelling + GA + genetic .

The obtained responses from the last fifteen years (since 2010), grouped by the publication date, are presented in Figure 1.

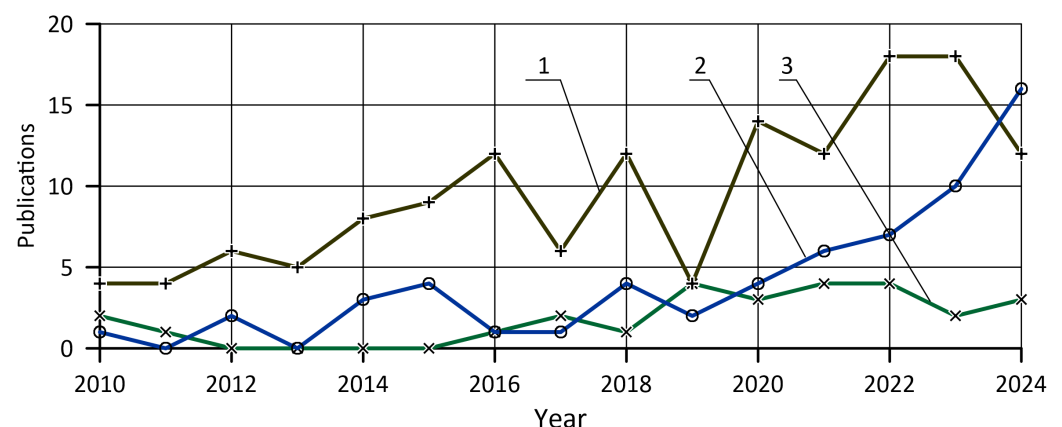


Figure 1. Number of publications on liquid sloshing modelling: 1—traditional methods; 2—neural network usage; 3—genetic algorithm applications.

As it arises from the figure, a significant increase in interest regarding liquid sloshing modelling using neural networks, including machine learning and deep learning, has been observed in recent years. In 2024, the number of neural network-related publications exceeded the number of articles based on traditional, deterministic methods for the first time. In turn, during the last several years, the number of publications on deterministic

modelling methods, including CFD and related, remains at a similar level. A few articles related to genetic algorithms are also starting to appear each year.

As for the types of publications, in the area of traditional deterministic methods, as well as genetic algorithms, the vast majority are research articles, 97% and 83%, respectively. However, in the area of neural network applications, research articles are only 42%, while as much as 41% are conference materials and almost 12% review articles. The remaining consists of a few book chapters and short communications.

In turn, the subject areas of the publications include mainly engineering (47% in total), environmental sciences (18%), and energy (13%). In addition, the papers are concerned with fields such as mathematics, computer science, Earth and planetary science, and chemical engineering.

3. Detailed Publication Analysis

The analyses were carried out taking into account the division of liquid sloshing modelling methods into three main categories. The first category included traditional mesh-based methods (FEM, FVV), especially computational fluid dynamics (CFD) and related ones, such as Volume Of Fluid (VOF) and fluid–structure interaction (FSI). The second group included other deterministic methods, including Concentration Mass Models (CMMs), Multiparticle (meshless), and using image analysis algorithms, as well as experimental verification and validation of the obtained numerical results. Finally, the third group includes research using AI methods, including genetic algorithms and artificial neural networks with convolutional architecture, deep learning, and machine learning.

3.1. CFD-Based Methods in Flow Modelling

The CFD methods are widely used in flow modelling. They allow for an accurate representation of fluid dynamics under various operating conditions. These methods are based on numerical solutions of the Navier–Stokes equations and analyse parameters such as flow speed and pressure distribution, considering viscosity and turbulence phenomena. An important aspect of these models is the consideration of hydroelastic effects, which influence the interaction between liquid sloshing and the flexibility of tank structures. The influence of flexible fluid–structure interactions on sway-induced sloshing has been extensively studied, demonstrating that tank flexibility can significantly alter sloshing dynamics and reduce impact pressures [1]. One notable approach involves the Arbitrary Lagrangian–Eulerian (ALE) finite element method, which has been applied to simulate liquid sloshing, particularly in conditions where contact angle hysteresis plays a significant role, such as microgravity environments [2]. By analysing the output parameters at the free outlet in a tank equipped with horizontal partitions, Sanapala [3] demonstrated that the partition effectively reduces wave amplitude by dissipating energy. On the other hand, Zhang [4] analysed damping mechanisms through uninstalled baffles located at the bottom of the tank, finding that using such safeguards leads to the effectual dissipation of the liquid’s kinetic energy. Research results indicate that pressure distribution varies depending on the excitation force and resulting wave amplitude. Pujari and Rajan published similar outcomes [5], analysing the damping rate of free oscillations in three selected reservoirs. The results showed that the presence of baffles significantly increased energy dissipation, effectively reducing sloshing effects. On the contrary, Arslan et al. [6] indicated that the key reason for partitions is to improve stability and reduce impact during an emergency impact of a land vehicle. A typical CFD method usage diagram for liquid sloshing simulation is shown in Figure 2.

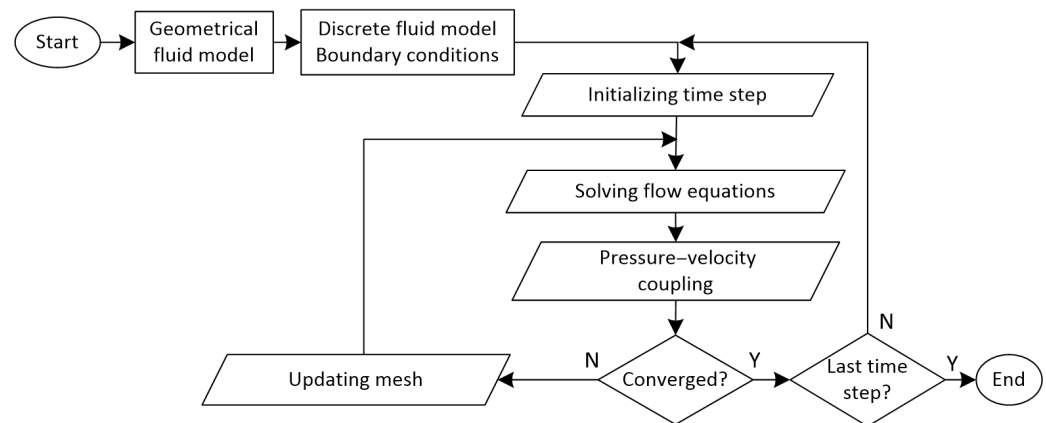


Figure 2. A diagram of CFD method usage for liquid slosh modelling.

3.1.1. CFD-FSI Methods

Traditional CFD methods can be effective in analysing fluid movement. Still, they ignore the influence of the tank itself, the deformation of its walls, or the impact of the liquid on its structural elements. FSI numerical models are used to consider these aspects, mainly where the interaction of liquids with the tank structure must be considered [7]. Recent studies have demonstrated that fluid–structure interaction (FSI) plays a significant role in sloshing behaviour, particularly in flexible tanks subjected to external forces and in scenarios involving multi-layer liquid interactions, where nonlinear effects significantly impact vessel dynamics [8,9]. Furthermore, the influence of external forces and phenomena, such as seismic vibrations or the acceleration and braking of the vehicle itself, can be included in the model. In Nouri’s research [10], a dynamic FSI model was described for simulating sloshing in cylindrical tanks. The liquid in these tanks is a network of interconnected spring–damper–mass systems. As a result, forces acting on the tank walls and, thus, the walls’ deformation were predicted. A similar approach was used by Wang et al. [11], carrying out numerical and experimental analyses of the influence of a flexible membrane on the sloshing phenomenon in horizontal tanks. The authors proved that adding a membrane can prevent resonance in partially filled tanks and significantly reduce the amplitude of liquid oscillations. The development of the bidirectional FSI model by Rossetti [12] and the use of flexible baffles confirm that the increased flexibility of the baffles improves the liquid oscillations’ damping. This results in a significantly lighter and more effective system for reducing sloshing, among others, in transport. Additionally, following the research conducted by Cao [13] on the influence of flexible partitions on the dynamics of sloshing in tanks subjected to excitation, it can be noticed that partitions with variable stiffness can effectively reduce the sloshing amplitude. Furthermore, the results show that this approach can also minimize the stresses on the tank walls. A diagram showing the algorithm of CFD method usage with the FSI approach for liquid sloshing simulation is presented in Figure 3.

Flexible structures such as fuel tanks, aircraft tanks, or LNG tanks may be highly susceptible to wall deformation, which negatively affects both the dynamics of the liquid and the stability of the structure. Kha [14] showed the real influence of the cylindrical tanks’ elasticity on the wave height. Furthermore, he analysed structural deformations under the influence of seismic loads, revealing that the increased wall flexibility causes an increase in the wave height. However, at higher tank filling levels, the structure deformation decreases. The use of damping elements, such as floating foams proposed by Barabadi [15], can effectively reduce both the wave height and kinetic energy of wave oscillations. Turner [16] achieved similar effects using partitions with controlled flexibility, which reduced the wave amplitude by 30–50%. In turn, Xue et al. [17] emphasized the importance of heterogeneous materials or tank structures, demonstrating that using materials with adjustable permeabil-

ity can effectively reduce tank wall stresses and wave amplitude. Additionally, Xue focused on using heterogeneous construction materials to design the tank walls. Similar results were obtained by Belahsen [18], who proposed composite walls with variable stiffness, which more effectively damped vibrations and minimized FSI effects. On the contrary, Aderaw and Nallamothe in [19] showed that changing the tank geometry and its position on the vehicle not only improves its stability but also reduces roll moments resulting from liquid–wall interactions.

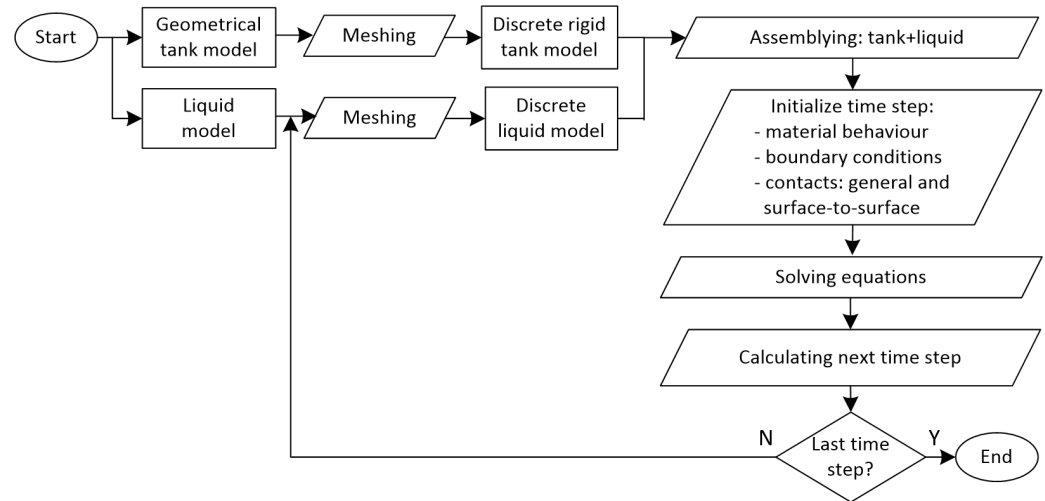


Figure 3. Diagram representing the CFD method with FSI approach for liquid sloshing simulation.

3.1.2. CFD-VOF Methods

The recent development in computing power technologies enables such methods for increasingly complex problems, including predicting liquid behaviour in tanks, mobile containers, or pipelines. On the other hand, the shape and geometry of a tank may be crucial to the dynamics of liquid ripples. Research results indicate that different shapes of tanks cause various behaviours of the free surface of the liquid and also affect wave amplitudes, resonance frequencies, and dynamic forces acting on the walls. In Wang’s research [20], the VOF (Volume of Fluid) method and dynamic meshing were used to analyse sloshing in a rectangular tank. The result revealed that the free height of the liquid does not always occur in areas of maximum shock pressure. Numerical analyses using the VOF method by Liu and Lin [21] showed that partitions with an appropriate configuration can significantly reduce the effects of waves and improve the stability of the entire structure. The studies also confirmed that vertical baffles inside cylindrical tanks can effectively decrease the intensity of wave action and reduce the force of liquid impact on the walls. Wu and He in [22] analysed the influence of geometry on wave intensity in rectangular tanks equipped with various configurations of vertical baffles by the VOF method. They showed that an increase in the number of partitions effectively reduces the wave amplitude, and optimal damping is achieved when the height of the partitions is adjusted to the liquid level in the tank. The best damping occurs with partitions equal to the height of the liquid, while at low filling levels, partitions higher than the liquid level are more effective, while at medium levels, slightly lower ones are more effective. Likewise, research by Huang [23] confirmed that the height of partitions, their position, and their number can significantly affect wave attenuation, and that the reduction in the intensity of liquid impacts on the walls of the structure is influenced by the height of the partitions, which can change the resonance frequencies. Another similar research conducted by Huang [24] pointed out that additional partitions in the tank may significantly reduce the height of the free-surface wave and impact force between the liquid and tank walls.

Studies conducted by means of the VOF method for cylindrical tanks have shown more complex wave dynamics, especially in the case of extreme accelerations. In particular, Kim and Kim in [25] showed that in the case of cylindrical tanks, the location of internal pipes and the arrangement of partitions are crucial, which can effectively limit the wave amplitude and dampen dynamic forces. The authors revealed a relationship between the liquid height and the nature of the ripples, where at low fill levels, waves are chaotic. In contrast, at higher levels, they stabilize but do not eliminate chaotic behaviour permanently. Similarly, Topçu and Kılıç [26] used annular baffles in cylindrical tanks, which decreased the turbulence level and reduced the wave height, while Chu et al. [27] indicated that the use of multiple partitions in a cylindrical tank allowed for more effective damping of waves than single partitions. The results are significant in the design of movable tanks for the chemical and oil industries, which require a high level of liquid stabilization. Furthermore, Ma [28] proposed an approach based on data-driven algorithms to identify the parameters responsible for modelling large sloshing amplitudes. The method was designed for precise mapping of the influence of forces on the behaviour of liquids and enabled better optimization of the transport tank design. Experimental research conducted by Wang [29] showed that the use of baffles in vehicle tanks could increase the base wave frequency by up to 50–200%. In numerous cases, this may reduce the risk of resonance but, at the same time, shift the resonance to a different frequency range. In turn, Ünal et al. [30] conducted a numerical analysis of the influence of T-shaped partitions in a two-dimensional tank subjected to oscillatory excitation. The results indicated that baffles with a height of 80% of the liquid level are the most effective in suppressing waves and significantly reducing the dynamic pressure on the tank walls.

The forcing frequency plays a key role in the wave intensity. Cai et al. [31] performed numerical simulations using the VOF method for transport tanks equipped with various configurations of transverse partitions, analysing the impact of forcing forces on wave attenuation. The studies showed that partitions with 30% holes could cause changes in the maximum impulse value by up to 31%, depending on the shape of the partition, which highlights the importance of optimizing their geometry. Similar results were obtained by Akyıldız and Ünal [32], who used the same method to analyse three-dimensional ripples in a rectangular tank subjected to different forcing conditions. Their research showed that sloshing resonance may occur for specific ranges of excitation frequencies, but its effects depend on the tank's geometry and the presence of partitions. Also, Kumar and Choudhary [33] analysed sloshing frequencies in a baffled tank for various filling levels using Ansys software.

3.2. Concentration Mass Model Utilization

The mass concentration model (CMM) is a simplified approach that may be applied to sloshing analysis, replacing CFD-based methods while significantly lowering computational costs. Using Lagrange's equations, CMM models capture important dynamic features while treating the fluid as a collection of concentrated masses joined by springs and dampers. The CMM models, among others, are used to analyse large reservoirs due to the possibility of reducing the degrees of freedom in numerical simulations. The effectiveness of the CMM method was demonstrated by Yoshitake et al. [34], presenting a two-dimensional mass concentration model for the analysis of nonlinear ripples in a rectangular tank. The research demonstrated high compliance with theoretical models in terms of natural frequencies and mode shapes in rectangular tanks. The study conducted by Lu et al. [35] analysed the influence of the tank filling level (10%, 50% and 90% of the total volume) on the sloshing dynamics and showed that different filling levels lead to significant changes in the forces acting on the tank walls. The analysis showed that the

maximum values of wave forces and amplitudes occur at a filling level of 50%, which is an essential factor in the design of tanks subject to dynamic loads. Additionally, research on the dynamic properties of CMM models confirmed their effectiveness in nonlinear wave analysis. The work of Sahaj et al. [36] demonstrated that the reservoir's scale and proportions significantly impact the wave intensity, which is crucial for the correct model calibration. In turn, research by Daneshmand et al. [37] on cylindrical tanks showed that CMM models can effectively be used to analyse sloshing in horizontal reservoirs subjected to harmonic and seismic excitations. The analysis showed that the forces acting on the walls of a cylindrical tank are, in some cases, higher than in a rectangular tank of comparable volume, which is crucial when designing tanks subject to dynamic loads. In contrast, the limitations of CMM models include difficulties in mapping irregular reservoirs and the impact of large deformations of the liquid surface on the accuracy of calculations. Yoshitake et al. [34] emphasized that tanks with irregular shapes require additional methods for reducing the degrees of freedom, which limits the possibility of directly applying CMM without extra calculations. Moreover, analysing nonlinear waves, especially with sudden changes in tank movement, requires additional modifications to the numerical models.

3.3. Multiparticle Methods in Sloshing Analysis

Multiparticle methods, also referred to as meshless, constitute an advanced computational technique for fluid dynamics modelling in tanks. They ensure easier handling of large free-surface deformation problems when compared to traditional mesh methods, such as FVM or CFD. They may be especially helpful in analyses of nonlinear phenomena like wave refraction, vortex generation or the interaction between the liquid and the structure of a tank. The most commonly used multiparticle method variants include Moving Particle Semi-Implicit (MPS) and smoothed particle hydrodynamics (SPH). Huang and Wang et al. in [38] demonstrated that the MPS method better approximated real liquid behaviour than FVM, most notably in simulations demanding an accurate depiction of dynamic forces and wave damping. Furthermore, they showed that MPS can capture nonlinear effects such as liquid rotation and intense vortex formation near the tank walls. In turn, the research conducted by Zhang and Wan [39] described a new technique which used classical FEM together with the MPS techniques to directly simulate fluid–structure interactions and capture wave effects more accurately. The paper presented a structured mesh for free-surface modelling, allowing for a more accurate calculation of restoring forces and wave properties. Furthermore, Jena and Biswal [40] conducted a numerical study on the violent liquid sloshing phenomenon in a partially filled rectangular container by the MPS method, including five modifications to the original version. The proposed model was successfully applied to a partially filled tank undergoing horizontal sinusoidal excitation. The sloshing wave amplitudes and pressure on tank walls were calculated. Next, the assessment of dynamic behaviour in base shear, overturning moment, and impact pressure load exerted on tank ceilings induced by violent sloshing motion has been demonstrated.

3.4. Nonlinear Models of Sloshing Phenomenon

The sloshing phenomenon, especially in partially filled tanks, is a complex dynamic process involving large free-surface deformations and extensive liquid–structural interactions. Strong dynamic forces, variable boundary conditions, or irregular reservoir geometry require accurate modelling of these phenomena, making nonlinear models an essential component.

For example, multimodal models proposed by Zhao et al. [41] include the contributions of higher eigenmodes to wave formation and interactions with the reservoir geometry. This permits the free-surface refraction and the nonlinear pressure on the walls to be mapped. In

turn, the study by Chen et al. [42] achieved a tight agreement with experimental data due to employing nonlinear models in MATLAB R2023, particularly in the domain of high wave amplitude. Instead, Cho et al. used their own-developed FEM program [43] to carry out resonant sloshing analysis in the frequency domain and obtain damping characteristics of a rectangular, partially filled tank. The work of Balaş et al. [44] explored the effects of sudden braking on the flow dynamics of fluids in the tanks and demonstrated that nonlinear models must be used to capture phenomena appropriately, including the sloshing noise, as well as the fluid–tank wall interaction. In numerous works, nonlinear models were built to set and optimize the arrangement of vertical partitions inside the tank. The effectiveness of vertical partitions depending on their porosity, arrangement in the tank, and immersion depth based on a nonlinear model was demonstrated by Cho and Kim [45]. The importance of the partitions' arrangement, including safety issues, was proven by Ayiehor [46] by means of a study using nonlinear models of land transport tanks. According to these studies, partitions with holes evenly distributed throughout the volume were more effective than traditional solid partitions. Similar results were presented in a PhD thesis by Kumar [47], who carried out comprehensive studies and proved that using vertical partitions significantly improves the tank's stability. Kumar's simulations showed that baffles with variable porosity could reduce wave amplitude by up to 40–50% compared to traditional rigid baffles. As the outcomes revealed, the best results were achieved by placing partitions at strategic points of the tank. Cho [48], in turn, proposed the use of flexible porous partitions as a lightweight alternative to rigid partitions. As shown by numerical analysis, the use of such partitions not only significantly reduced the mass of the tank but also dissipated energy, similar to rigid partitions. Another study analysing the safety and on reducing the risk of overturning transport tanks involved the development of a multi-stage pendulum for real-time sloshing monitoring, conducted by Qi [49].

3.5. Image Processing and Visualization in Sloshing Analysis

Image processing plays a significant role in sloshing research, providing the possibility of precise fluid dynamics analysis inside tanks. The basic methods applied for image analysis are Particle Tracking Velocimetry (PTV), which is based on putting markers either onto a liquid surface or in its volume to track their motion, and Second Edge Detection, which depends on independent surface detection algorithms, such as Canny or Sobel. Still, in research, enhanced methods are deployed, such as the Segment Anything Model (SAM) proposed by Peng et al. [50], where video images independently identify the profile of waves or the Simultaneous Multiplicative Algebraic Reconstruction Technique (SMART) developed by Tödter et al. [51] to quantify multiphase flows during sloshing. The studies of Ren et al. [52] demonstrated that image processing techniques allow for the precise tracking of fluid dynamics, which is particularly important in the case of irregular excitations and interactions of the fluid with elastic partitions. Image processing enabled the analysis of air entrainment and the formation of turbulence around the partitions, which influenced the accuracy of the assessment of wave attenuation. Furthermore, Liu et al. [53] performed extensive studies of sloshing in rectangular tanks subjected to tilting excitations using image capturing and processing techniques. Liu pointed out the key role of filling parameters and resonance frequencies. Spectral analysis has shown that for 70% of the filling level, a shift in the resonance frequency may occur, which can indicate nonlinear liquid vibrations. Advanced visualization techniques can also be used to analyse the liquid sloshing and the interactions between liquid and partitions. Wu and He [54] applied the Particle Image Velocimetry (PIV) method to the internal flows in a tank with vertical baffles, demonstrating the change in the flow structure and decrease in the near-wall liquid velocity, which confirmed their effectiveness in suppressing wave action.

To summarize, compared with traditional measurement techniques, such as pressure sensors or point probes, imaging techniques provide simultaneous monitoring of several points on the liquid surface, enhancing the accuracy of the analysis. Furthermore, image processing can detect nonlinear effects such as vortex formation or changes in wave profile over time. In this case, the research process usually includes several steps: First, high-resolution cameras record the fluid motion with a rate of acquisition adapted to the system dynamics, e.g., 100–1000 frames per second. Further, images are transformed into a series of frames and subsequently processed through noise filtration, thresholding, and morphological transformations. On this basis, marker trajectories, wave amplitudes, and fluid flow velocities are identified and compared with the results of numerical simulations.

3.6. AI-Based Techniques in Sloshing Analysis

Artificial Intelligence (AI) has become an essential tool in fluid dynamics modelling, offering significant improvements in prediction accuracy, optimization of mitigation strategies, and computational efficiency compared to traditional numerical methods. Among AI techniques, machine learning (ML) has gained particular attention due to its ability to analyse complex patterns in sloshing behaviour. It is important to clarify that artificial neural networks (ANNs) are a subset of ML and should not be used interchangeably with the broader term “machine learning”. ML encompasses a wide range of techniques beyond ANNs, including decision trees, support vector machines (SVMs), reinforcement learning, and fuzzy logic, all of which can contribute to fluid dynamics modelling in different ways. While this study primarily discusses ANN-based approaches, other ML techniques also play a role in predictive modelling and optimization.

Despite these advancements, AI applications in sloshing modelling remain an emerging field. Recent studies suggest that further exploration is needed to fully integrate AI with fluid dynamics, particularly in the context of data fusion and predictive modelling. Zhao et al. [55] provide an extensive review of deep learning-based data fusion methods, emphasizing their role in combining heterogeneous datasets to improve predictive accuracy. While their study focuses on medical applications, similar approaches can be applied in fluid dynamics by integrating experimental and numerical data to enhance the robustness of AI-driven simulations. Additionally, Liu et al. [56] introduced an AI-based fault detection method that utilizes Extreme Learning Machines (ELMs) in combination with numerical simulations. Their approach highlights how AI can optimize predictive models and improve system diagnostics, which could be beneficial in sloshing mitigation strategies and adaptive control systems. A flowchart of a typical machine learning model based on the feed-forward ANN is shown in Figure 4.

In addition to ANNs, other AI-based approaches such as reinforcement learning (RL) and fuzzy logic have shown promise in sloshing-related applications. RL techniques have been successfully applied in adaptive control systems for fluid–structure interaction, optimizing real-time control mechanisms to minimize sloshing effects. By continuously adjusting control parameters in response to changing sloshing conditions, RL-based strategies can enhance the stability of liquid storage tanks and fuel transportation systems. Recent advancements in RL-based fluid dynamics optimization have demonstrated its potential in reducing structural loads and improving energy efficiency in dynamic environments.

Fuzzy logic, on the other hand, provides a rule-based approach to managing uncertainty in fluid dynamics modelling. Unlike traditional deterministic models, fuzzy systems can process imprecise data and make adaptive decisions based on expert-defined rules. In sloshing analysis, fuzzy logic controllers have been implemented to dynamically adjust damping mechanisms in liquid containers, particularly in maritime and aerospace applica-

tions. These controllers improve stability by responding to real-time sensor data, reducing the risk of excessive fluid motion in variable operating conditions.

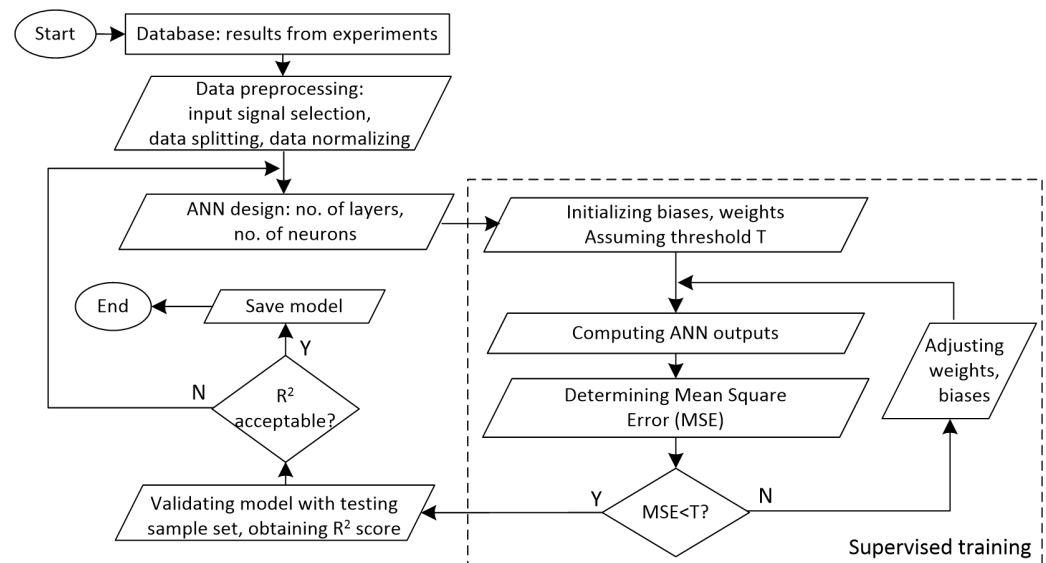


Figure 4. Machine learning model diagram for liquid sloshing simulation based on ANNs.

Furthermore, convolutional neural networks (CNNs) have emerged as powerful tools in image-based sloshing analysis. CNNs are particularly effective in feature extraction from experimental and numerical visual datasets, allowing for the classification of free-surface wave patterns, impact loads, and turbulence regions. U-Net, a specialized CNN architecture, has been widely utilized for high-precision segmentation and reconstruction of free-surface dynamics. By training U-Net models on large experimental datasets, researchers can enhance the accuracy of predictive sloshing simulations, reducing the reliance on computationally expensive CFD models.

As AI continues to evolve, future research should focus on refining its integration with classical computational methods. In particular, the application of Physics-Informed Neural Networks (PINNs) for incorporating governing equations into AI models and the use of metaheuristic optimization techniques for structural improvements in tank designs remain promising directions for further investigation.

3.6.1. Feed-Forward Neural Networks and Machine Learning Methods

AI-based techniques, particularly feed-forward neural networks (FNNs) and other machine learning (ML) methods have been applied in sloshing analysis to enhance prediction accuracy, reduce computational complexity, and optimize sloshing mitigation strategies.

- **Nonlinear sloshing modelling:** A machine learning-based characterization framework can be developed for nonlinear sloshing representation. This approach, proposed by Luo et al. [57], uses sequential learning and sparse regularization to categorize sloshing dynamics into linear evolution and nonlinear forcing. By embedding sloshing sequences into a high-dimensional phase space and performing spectral decomposition, the framework can efficiently model chaotic dynamical behaviours such as signal bursting and switching.
- **Sloshing prediction:** Feed-forward ANNs may be applied in a liquid flow modelling system, where they are used alongside regression models to optimize flow predictions. This method usually integrates experimental data and machine learning algorithms, ensuring a balance between computational efficiency and predictive accuracy. The study by Dutta et al. [58] highlights how AI can enhance real-time liquid flow estimation by overcoming the challenges posed by system complexity and computational

limitations. The following study by Kim et al. [59] presents an ANN used to predict the sloshing loads under varying operational conditions. This approach helps forecast extreme sloshing loads and provides insights into the dynamic response of sloshing-induced wave impacts. Deep learning, specifically Residual Neural Networks (ResNet), was employed to predict sloshing pressure based on wave image data. This ensures high accuracy in predicting peak pressure in resonance regimes, critical for structural safety assessments of liquid-filled containers. Similarly, Chegini et al. [60] used the designed ANN for load prediction due to their ability to model nonlinear fluid–structure interactions. In contrast, Liu [61] designed a deep neural network for image preprocessing and wave-breaking recognition, improving segmentation accuracy in real-time experiments. In turn, Men et al. [62] proposed a hybrid, neural net-based system for liquid storage tank seismic damage estimation, while Hoseini [63] designed a deep learning neural network for stirred tank foam detection.

- Design optimization for sloshing suppression: ANN-based models can be applied to optimize porous baffle design for sloshing mitigation in a swaying rectangular tank. The model created and trained by George et al. [64] utilized an extensive dataset of baffle arrangements, porosity levels, and motion characteristics. The results demonstrated that ANNs can effectively predict the optimal baffle configuration while minimizing sloshing impact forces.
- Signal processing: A study on fuel-level measurement in dynamic environments employing a feed-forward backpropagation ANN (BPNN) to process capacitive sensor signals was carried out by Terzic et al. [65]. As a result, a significantly lower error rate (0.11%) was achieved compared to traditional averaging methods. In turn, Nerattini [66] designed a neural network-based optimal fuel-usage strategy for an aircraft which maximizes the beneficial effects of wing-tank sloshing-induced damping. ANNs have also been leveraged for extreme load prediction in sloshing experiments, where large experimental databases were processed using neural networks optimized through hyperparameter tuning. This approach facilitated improved generalization and reliability of predictive models [67].
- Fluid dynamic simulation: This subject area includes calibrating viscous damping parameters for nonlinear sloshing models. Zhang et al. [68] conducted a study on floating liquefied natural gas (FLNG) tank simulations, introducing an adaptive ML-based strategy using neural networks to dynamically calibrate damping coefficients, ensuring improved representation of physical reality in numerical models. Furthermore, graph neural networks (GNNs) have been integrated with incompressible smoothed particle hydrodynamics (ISPH) by Zhang et al. [69] for free-surface flow simulations, demonstrating significant reductions in computational time compared to conventional solvers.
- Other peculiar applications of deep ANNs include a three-tank system fault diagnosis proposed by Irani [70] and a fuzzy deep neural sliding mode controller for automatic liquid level control in a quadruple spherical tank system by Ashwini et al. [71].

3.6.2. Convolutional and U-Net Networks

Convolutional neural networks (CNNs) and their specialized architectures, such as U-net, have been successfully implemented for free-surface identification in sloshing experiments:

- CNNs can be used for feature extraction and segmentation of liquid wave surfaces based on high-resolution imagery. They help to identify key aspects of wave behaviour [72], including breaking waves and turbulence, by processing a large volume of experimental and synthetic image data. They can also be utilized to accelerate numerical simulations and improve spatial feature extraction.

- Deep CNNs are utilized to improve the precision of free-surface tracking by integrating direct linear transformation (DLT) and contour detection techniques. Liu et al. [61] enhanced the detection of wave-breaking thresholds and significantly refined the segmentation accuracy compared to conventional optical measurement approaches. In turn, Shen et al. [73] used CNNs for tracking the free-surface dynamics in liquid tanks. The designed network processes image data from sloshing experiments and helps in detecting wave-breaking patterns and fluid behaviour.
- Recently, CNNs have been applied to replace the pressure Poisson equation (PPE) solver in fluid simulations, significantly reducing computational load while maintaining accuracy [69]. Moreover, deep learning architectures incorporating convolutional layers have been employed in buckling strength prediction for liquefied natural gas (LNG) containment systems under sloshing loads. This approach facilitated the development of an optimized ANN model for assessing the structural integrity of LNG cargo tanks by Park [74], considering highly nonlinear dynamic buckling responses.

U-Net is a specialized convolutional neural network that has been effectively applied in sloshing analysis to segment and reconstruct free-surface behaviour in liquid tanks:

- A U-Net may be trained on experimental datasets to enhance its predictive capability, as proposed by Wei [72]. Wei validated the effectiveness through direct comparisons with physical hydrodynamic experiments, showing its robustness in sloshing load prediction models. In particular, he demonstrated that U-Net's encoder–decoder structure enables it to extract hierarchical features from images, helping to reconstruct high-resolution wave maps.
- The encoder–decoder structure of U-Net allows for the precise extraction and reconstruction of wave characteristics, providing high-resolution sloshing prediction, as demonstrated by Ahn et al. [75]. Furthermore, an experimental study of liquid slamming in elastic rectangular tanks investigated the interaction between the fluid and structure during high-impact sloshing events [73].

3.6.3. Optimization of Ship Subdivisions and Tank Designs

The design of ship subdivisions and tank layouts plays a crucial role in minimizing liquid sloshing effects. Advanced optimization techniques have been widely applied to enhance stability, reduce structural loads, and improve fuel efficiency in marine and aerospace applications.

Several computational techniques have been employed for optimizing sloshing mitigation structures:

- Genetic Algorithms (GAs): GA-based approaches are extensively used to optimize ship subdivision and tank design by exploring multi-variable solution spaces. Saghi et al. [76] demonstrated that GA-optimized sloshing mitigation structures provided effective suppression of free-surface oscillations, improving load distribution.
- Multi-objective optimization: Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been applied to optimize baffle configurations in automotive water tanks, reducing wave height and mitigating liquid agitation caused by pump-driven flows [77].
- Machine Learning-Based Approaches: Multi-Gene Genetic Programming (MGGP) has been used to develop predictive models correlating sloshing-induced pressure variations with liquid height, achieving high accuracy with reduced computational costs [78].

Furthermore, the integration of **deep reinforcement learning (DRL)** and **genetic algorithms** has enabled the adaptive tuning of nonlinear feedback controllers for slosh-

ing mitigation [79]. This hybrid approach provides a promising solution for real-time optimization of liquid damping mechanisms in dynamic environments.

By leveraging these optimization techniques, ship designers can significantly reduce sloshing-induced instabilities, leading to improved operational safety and efficiency in marine and aerospace industries.

4. Discussion: Methods, Types and Current Trends in Liquid Sloshing Modelling

This section summarizes the geometry of the analysed tanks, numerical methods and types of dynamic models used, methods of experimental validation of the results, and the degree of use of AI methods in liquid slosh modelling.

4.1. Numerical Simulation Methods and Types of Dynamic Models

In terms of geometry, rectangular and cylindrical tanks are most frequently analysed. However, there are also works on spherical, elliptical, prismatic, or more complex shapes, such as fuel tanks. A summary of tank geometry is presented in Table 1.

Table 1. Geometry of the analysed tanks.

Shape	Rectangular 2D	Rectangular 3D	Cylindrical 2D, 3D	Spherical 3D	Elliptical 3D	Prismatic 3D	Complex e.g., Fuel Tanks
Deterministic methods	[3,4,13,18,20] [22,27,30,34,43] [16,42,45,48]	[5,12,15,20,24] [17,21,32,33,54] [44,47,50,52,53] [36,51]	[10,11,14,25,47] [29,31,35,37,41] [46]	[23,28,38]	[46,49]	[26]	[6,19]
AI-based methods	[60,61,69,73,76] [63,66,68,79]	[57,59,64,72,78] [70,74,80]	[58,62]	[71]		[75]	[65,67,77]

A similar comparison concerning anti-sloshing partitions and baffles is shown in Table 2. The most commonly used are simple, flat vertical baffles reaching a certain height or porous baffles filling the entire tank cross-section. Horizontal baffles or baffles of a more complex shape are used less frequently. Some works, especially those using AI methods, are concerned with studying liquid movement in tanks without baffles.

Table 2. Partitions and baffles in the analysed tanks.

Shape	Vertical Solid	Vertical Porous	Horizontal	T-Shaped Vert+Horiz	Other Solutions	No Baffle
Deterministic methods	[6,13,14,24,26] [19,22,27,29,31] [21,46]	[16,17,45,48]	[3,12,33,43,47] [52]	[30,32]	[4,11,15,18,44]	[5,10,20,28,54] [23,25,35,50,53] [34,37,38,41,42] [36,49,51]
AI-based methods	[57,69,77]	[64]				[58,59,72,73,75] [60–62,76,78] [63,65,67,74,79] [66,68,70,71,80]

Considering that the vast majority of the presented works use mathematical modelling and computer simulation methods, Tables 3 and 4 present a summary of the software used in research by deterministic and AI-based methods, respectively. It should be noted that numerous authors do not provide information about the modelling and simulation software they utilized.

Table 3. Most popular software used in research by deterministic methods.

Software	Ansys Fluent	Matlab Simulink	OpenFOAM	Abaqus Maple	Analytical Solution	In-House Other
Deterministic methods	[4,6,12,20,24] [18,19,26,30,54] [25,31,33,35,42,47]	[35,41,44,49]	[3,5,14,17,29]	[10,15,41]	[13,16,45,48]	[11,21,27,28,32] [23,37,38,43,46,51]

It can be observed that ANSYS/Fluent is the most popular among commercial systems, while OpenFOAM is a well-known open-source software. Furthermore, in-house developed, dedicated software is also used in some research.

Table 4. Most popular software used in AI-assisted research.

Software	Matlab Simulink	Python and Libs	OpenCV	OpenFOAM LabView	Other Prog. Lang	In-House Specialized
AI-based software	[58,60,66,71,72] [63,65]	[58,61,64,69,79] [62,63]	[61,63,64,72]	[59,65,78]	[59,67,73]	[68,70,75–77]

As seen from Table 3, Python programming language, with its specialized libraries for artificial neural network design and training (PyTorch, TensorFlow), as well as Matlab system, including Simulink, Neural Network Toolbox, and ANFIS editor, are the most commonly used tools for modelling liquid sloshing with the help of AI techniques.

4.2. Comparative Analysis of Sloshing Modelling Techniques

To better understand the differences between sloshing modelling approaches, a direct quantitative comparison is necessary. Table 5 summarizes the strengths and limitations of traditional and AI-based methods in terms of computational cost, accuracy, and applicability.

Table 5. Comparison of sloshing modelling techniques.

Method	Computational Cost	Accuracy	Applicability	Limitations
Computational Fluid Dynamics (CFD)	High	Very High	Highly detailed flow simulations	Requires extensive computational resources
Finite Element Method (FEM)	High	High	Structural analysis of tanks under sloshing loads	Less suited for real-time applications
Smoothed Particle Hydrodynamics (SPH)	Medium	High	Capturing free-surface deformations	Computationally intensive for large-scale models
Artificial Neural Networks (ANNs)	Low–Medium	Medium–High	Fast approximation of sloshing effects	Requires large training datasets
Convolutional Neural Networks (CNNs)	Medium	High	Image-based sloshing detection	Limited generalization to unseen cases
Reinforcement Learning (RL)	Medium	Adaptive	Real-time control of sloshing mitigation	Requires real-time feedback mechanisms
Fuzzy Logic	Low	Moderate	Decision-making and real-time adjustments	Difficult to model highly complex dynamics

The differences between these methods become more apparent when applied to specific case studies. Three practical examples highlight the advantages and limitations of each approach.

In the case of sloshing-induced pressure on tank walls, CFD provides the most detailed pressure distribution data, making it the preferred choice for structural integrity analysis. However, it is computationally demanding and unsuitable for real-time applications. AI-based models, such as CNNs and U-Net, can estimate pressure zones from past data, significantly reducing computational cost but lacking adaptability to unseen conditions. Reinforcement learning (RL) methods offer a dynamic solution, as they can actively adjust baffles or tank shapes to minimize pressure fluctuations in real time.

For real-time sloshing prediction in transport tanks, traditional CFD and FEM models are impractical due to their high computational cost. Instead, ANN-based models can predict sloshing behaviour in milliseconds, making them well suited for integration into on-board vehicle control systems. RL-based controllers can optimize braking and acceleration strategies to minimize sloshing-induced instability, improving fuel transport safety.

When considering sloshing in irregular geometries, such as aerospace fuel tanks, traditional CFD methods require complex meshing and long simulation times. SPH methods are particularly useful in these scenarios, as they handle large free-surface deformations more efficiently. AI-based models struggle with generalizing to unseen geometries unless they are trained on sufficiently diverse datasets.

Overall, the quantitative comparison in Table 5 highlights the trade-offs between traditional and AI-based sloshing modelling techniques. While CFD remains the gold standard for high-fidelity simulations, AI-driven methods provide faster, computationally efficient alternatives, making them ideal for real-time applications. Future research should focus on integrating AI techniques with physics-based simulations to achieve more accurate and adaptable sloshing models. Additionally, expanding AI training datasets and improving real-time monitoring techniques will enhance the reliability of these approaches in practical applications.

4.3. Experimental Validation Techniques

Laboratory experiments play a significant role in sloshing research work. They are used to help validate numerical models and ascertain the actual influence of various parameters on tank fluid dynamics. These experimental techniques can be classified based on dynamic pressure measurements, liquid motion visualization, PIV, and laser methods. The most used experimental methods are dynamic pressure measurements [6,10,14,20,21,25,30,39,40,50,53], which represent the forces on the tank wall due to the fluid in motion. These are usually acquired with piezoelectric sensors and pressure transducers that record real-time pressure changes. The experiments unveiled that the forces acting on the partitions and walls of the tank change with the liquid level and excitation parameters [6,19,20,25,30,49]. Visualization of liquid motion uses advanced techniques, including Particle Tracking Velocimetry (PTV), Particle Image Velocimetry (PIV), and images taken with high-speed cameras, which are used in the analysis of the shape of such ripples and the interactions between liquid and partitions. For example, the liquid-free surface's deformation in the vehicle fuel tank was recorded with a high-frequency video camera in the research performed by Wang in [29]. Image analysis allowed for a precise determination of the ripple amplitude and identification of nonlinear effects due to splashes and wall vortices. In turn, Wu and He [54] applied the PIV technique to the analysis of internal flows in a tank with vertical baffles, which enabled the measurement of the velocity magnitude and direction of liquid flow by following the particles suspended in the liquid and illuminated by a laser. The experimental results were compared with

CFD simulations, showing good agreement of the internal flows, especially in the area of wave contact with the baffles. Furthermore, advanced measuring techniques such as Laser Doppler Anemometry (LDA) and interferometry make it possible to precisely determine the flow characteristics of liquid and free surface deformation. This was used by Belahsen et al. [18] to investigate the effect of heterogeneous liquid density on wave dynamics of the free surface in tanks subjected to a sinusoidal excitation.

An essential stage during the sloshing phenomenon analysis is validating the created numerical models. It allows the assessment of the accuracy of the simulation and its compliance with actual conditions to be made. Model verification consists of comparing the results obtained in laboratory experiments with the results of numerical calculations. Examples of such calculations are FEM, CFD, and VOF methods, as well as AI model outcomes. Numerical model evaluation criteria for the validation utilized in the analysed publications include the following:

- Comparison of wave amplitude—An analysis of the maximum and minimum values of the free surface of the liquid in the tank, which are obtained from simulations and experiments.
- Dynamic pressure analysis—A comparison of the pressure distribution on the walls of the tank to determine the compliance of the numerical and experimental values of hydrodynamic forces.
- Liquid flow testing—The use of visualization techniques such as PIV and LDA to assess the compliance of the fluid motion trajectory.

4.4. Perspectives for AI Technologies

4.4.1. ANNs and Machine Learning

Machine learning (ML) techniques, particularly feed-forward neural networks and deep learning models, have significantly advanced sloshing analysis methods. These models enhance prediction accuracy, optimize mitigation strategies, and reduce computational demands compared to traditional numerical approaches. Integrating AI-driven models in sloshing research paves the way for real-time monitoring, adaptive control, and improved structural safety in liquid storage and transport systems.

It is important to emphasize that AI is a tool rather than a standalone solution. While AI-based models improve computational efficiency, they should be seen as complementary to traditional numerical techniques. AI helps address key challenges in classical methods, including high computational costs, difficulty in modelling nonlinear effects, and adaptation to dynamic conditions. AI-based models can act as proxy models to accelerate CFD simulations, learn from experimental data, and detect complex dependencies that traditional deterministic models may struggle with.

4.4.2. CNNs and U-Nets

The results suggest that AI models, including CNNs, U-Nets, and ANNs, significantly improve sloshing analysis by providing high-accuracy predictions of free-surface behaviour, impact loads, and hydroelastic responses. CNNs are particularly useful in feature extraction and image-based classification, while U-Net offers a robust framework for segmentation and reconstruction of free-surface dynamics. These AI-driven techniques facilitate real-time monitoring and predictive modelling of sloshing-induced loads, making them valuable tools for marine and transport applications.

4.4.3. Physics-Informed Neural Networks (PINNs) and Deep Learning in Numerical Modelling

A key advancement in AI-driven fluid dynamics modelling is the introduction of Physics-Informed Neural Networks (PINNs), which integrate fundamental physical equa-

tions into the learning process. PINNs offer several advantages, including improved model generalization, ensuring physically consistent predictions, and serving as fast surrogate models to reduce computation time. Unlike standard neural networks, PINNs require fewer training data as they incorporate governing physical laws, reducing the risk of non-physical results. In addition to PINNs, deep learning models have been increasingly used to reconstruct free-surface dynamics, analyse experimental image data, and reduce dimensionality in CFD simulations. These applications help improve computational efficiency without compromising accuracy.

4.4.4. Genetic Algorithms

Genetic algorithms (GAs) and their variants, such as NSGA-II and MGGP, are practical tools for optimizing sloshing mitigation structures and predicting sloshing loads. Their ability to efficiently search complex design spaces makes them valuable in structural optimization, parameter tuning, and empirical model development. The studies reviewed illustrate the broad applicability of GAs in predicting liquid sloshing behaviour, optimizing baffle configurations, and estimating hydrodynamic pressures in liquid storage systems.

4.4.5. Integrating AI with Traditional Numerical Methods

The future of AI in fluid dynamics modelling lies in hybrid approaches, where AI does not replace classical methods but enhances them. Several key integration strategies include AI-assisted CFD acceleration, optimization of sloshing mitigation structures, and experimental AI applications. Deep learning models can partially replace CFD solvers, reducing computational time, while AI-based optimization techniques help identify optimal tank geometries and baffle designs. Additionally, neural networks can process high-speed imaging data, automating the detection of key hydrodynamic phenomena such as wave breaking.

In conclusion, AI serves as a powerful enhancement to traditional modelling techniques rather than a substitute. Incorporating methods such as PINNs, deep learning, and hybrid approaches enables more efficient and accurate fluid dynamics simulations, leading to significant advancements in sloshing analysis.

5. Conclusions

This review article presents numerical methods recently used to study the modelling of fluid motion inside stationary and movable tanks, with special attention paid to artificial intelligence techniques. Of particular importance in this type of research is the determination of the energy of waves of a moving liquid, which can significantly impact the tank's stability and strength. Based on the findings from this review, the following detailed conclusions can be formulated:

- So far, deterministic algorithms, including CFD-VOF-FSI and related techniques and other nonlinear methods, are more commonly used in the modelling and analysis of liquid sloshing in tanks, accounting for approximately two-thirds of the analysed publications.
- AI-based methodologies, however, have demonstrated considerable advancements in sloshing analysis by enhancing predictive accuracy, computational efficiency, and system optimization. Feed-forward neural networks and machine learning techniques have improved load prediction and dynamic behaviour modelling.
- Convolutional ANNs and U-Net networks have been instrumental in reducing computational overhead for fluid simulations. Key benefits of U-Net in sloshing include accurate free-surface detection, enhanced real-time performance, and the ability to handle complex fluid motion. CNNs can also be used to extract wave contours from

high-resolution images, recognize sloshing wave behaviour in real-time, and improve segmentation accuracy compared to traditional optical methods.

- Genetic algorithms and reinforcement learning approaches have provided robust optimization frameworks for tuning model parameters, ensuring more precise and stable sloshing behaviour predictions. RL-based control systems have shown promise in dynamically adjusting tank movement strategies to reduce sloshing effects in real time, with potential applications in fuel management for aerospace and marine transport.
- The negligible contribution of fuzzy logic should be noted. Fuzzy inference rules have not been used so far to analyse liquid sloshing. Still, they could mainly expand the possibilities of controlling the tank movement to minimize sloshing amplitude or reduce the forces acting on the tank walls.
- The integration of Physics-Informed Neural Networks (PINNs) with classical CFD solvers offers a promising research direction. PINNs can accelerate numerical simulations by embedding physical laws into AI models, improving computational efficiency in large-scale simulations of sloshing-induced loads. Additionally, transfer learning techniques could enable the adaptation of AI models trained on general fluid dynamics problems to sloshing-specific tasks, reducing data requirements and enhancing predictive capabilities.

In general, AI-based innovations contribute to more reliable and efficient tank design solutions in transport, aerospace, automotive, and energy industries. In aerospace applications, AI-driven predictive models have been explored for optimizing spacecraft fuel slosh dynamics in microgravity environments. Similarly, AI-based optimization frameworks are being used in marine engineering to improve ship stability and cargo containment. The research of such technologies and their expansion may increase significantly in the near future.

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