Machine Learning-Enhanced Ultrasonic Velocity Measurement in Water

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Abstract
Ultrasonic velocity measurement in water has applications in flow monitoring, hydrometry, industrial process control, underwater acoustics, environment sensing and smart water infrastructure. Conventional ultrasonic systems such as transit-time, Doppler, multipath and sound-speed profiling systems provide non-invasive, continuous measurement. But, water property variations, flow instabilities, sensor geometry and signal degradation often affect their accuracy. Non-linear errors can be caused by temperature, salinity, pressure, turbulence, suspended particles, bubbles, path-length uncertainty and waveform distortion, and are not easily corrected by fixed empirical equations or conventional calibration. This review explores the potential of using machine learning to improve the measurement of ultrasonic velocity through calibration, environmental compensation, signal interpretation, sound-speed profile estimation, and real-time prediction. It brings together acoustic principles, traditional ultrasonic solutions, uncertainty factors, ML model families, signal processing solutions, compensation strategies, applications, comparative solutions, and future trends. The review suggests that machine learning should be used to augment the existing ultrasonic principles rather than replacing them. Its main strength is to complement traditional measurements via adaptive correction, powerful feature extraction, sensor fusion and uncertainty-aware prediction. Future ultrasonic water-measurement systems should integrate acoustic theory, robust instrumentation, data quality, machine learning that is interpretable, and deployment ready validation.

Keywords: Ultrasonic velocity measurement; Machine learning; Sound speed in water; Ultrasonic flow measurement; Intelligent sensor calibration

1. Introduction

The measurement of the velocity of ultrasonic waves in water is an important technique in acoustic sensing, hydrometry, industrial flow measurement, environmental monitoring and marine observation. The main advantages of this are that it is non-invasive, responds quickly, can be used continuously and can be used in the lab or field. In water-based systems, there are two related but different quantities that can be referred to as the ultrasonic velocity measurement. The first one is the speed of propagation of ultrasonic waves in water. The second is the velocity of the moving water as estimated by ultrasonic transit-time, Doppler or velocity-profile methods. The two forms are integral to the correct monitoring of water systems as they enable flow estimation, acoustic profiling, process control, resource management and smart sensing infrastructure. The value of reliable flow measurement in engineering and industrial systems has been quite clearly documented in the fluid-measurement literature (Baker, 2016).

The principle of the ultrasonic measurement is relatively mature. Transit-time systems use ultrasonic pulses to travel across a known acoustic path and the time taken for the pulses to travel is used to estimate sound velocity or flow velocity. Doppler systems measure velocity based on a frequency shift of the signals reflected by particles, bubbles or by something suspended in the water. Multipath and chordal-path arrangements are extensions of these concepts and provide a number of acoustic paths that are sampled, enhancing measurement in non-uniform flow fields. The ultrasonic flowmeter has been improved over a number of decades through improvements in the design of the transducers, electronic timing, signal processing and the installation architecture. Their performance, however, is still influenced by the properties of the water, the geometry of the sensors, the quality of the calibration and operating conditions (Lynnworth & Liu, 2006).

Even with these developments, traditional ultrasonic systems are susceptible to a number of sources of error. The velocity of sound in water is affected by temperature, salinity, pressure, dissolved solids and suspended particles. Turbulence, stratification, bubbles, wall effects and non-uniform velocity profiles are also factors affecting flow measurement. In addition, instrumental factors like transducer misalignment, unknown path length, sampling resolution, signal attenuation, coupling quality and sensor drift can also decrease the accuracy. These factors do not necessarily work independently from each other. For instance, temperature changes can affect the speed of sound and bubbles or turbidity can affect the waveform received and make the time of flight detection less sensitive. This complexity makes fixed empirical corrections and standard calibration curves to be less effective.

Machine learning is a potential method to improve the ultrasonic velocity measurement, as it can learn the nonlinear relationship between ultrasonic signals, environmental variables, sensor characteristics and reference measurements. The ML models can be used to estimate corrected velocity or improve the interpretation of the signals using the features of the waveforms, the time-of-flight values, the amplitude, the phase, the temperature, the salinity, the pressure, and the flow conditions, rather than relying solely on predetermined equations. ML can be used to assist with temperature compensation, sensor calibration, sound-speed profile reconstruction, signal denoising, drift correction and uncertainty-aware prediction. Machine learning is not an alternative to acoustic theory, in this context. It is an adaptive computational layer which can enhance the robustness of the measurement if physical equations and traditional signal-processing methods are not enough. In recent research on ultrasonic flow measurement, the importance of reconfigurable systems and deep-learning techniques to enhance the accuracy and adaptability of the flow measurement in complex measurement environments has been highlighted (Senthil Kumar et al., 2020).

The need for this review is due to the fragmented nature of literature. Research of sound velocity in water is frequently found in the fields of acoustics, oceanography and thermophysical-property research. Research on ultrasonic flow measurement typically falls under the categories of instrumentation, hydrometry and industrial metering. The applications of machine learning in the sensor calibration, acoustic signal processing, underwater prediction, remote sensing, and intelligent monitoring literature are presented. This means that there is no compact synthesis of the field which links the principles of acoustics to ultrasonic measurement systems, environmental error sources, ML-based correction methods and smart water applications. This gap is significant as recent research on machine learning for flow metering indicates an increasing number of data-driven models are used to solve nonlinear and multiphase measurement problems that are challenging to solve using conventional modelling alone (Bahrami et al., 2024).

The present review aims to discuss on an integrated basis the ultrasonic velocity measurement in water using machine learning. It first explains the difference between the acoustic sound velocity and ultrasonic estimation of water-flow velocity. It then examines the physical principles of ultrasonic measurement, traditional transit-time and Doppler systems, major sources of error, families of ML models, signal-processing techniques, environmental compensation techniques, and areas of application. The review also highlights the differences between empirical, signal-processing, data-driven and physics-informed approaches, to demonstrate where machine learning can be beneficial and where traditional measurement principles are still necessary.

The key point of this article is to present the hybrid intelligent ultrasonic velocity measurement in water. The stability of acoustic theory, reliability of well-designed instrumentation, and adaptability of machine learning are all needed to make accurate measurements. The use of ML-based systems can enhance the calibration, variability due to the environment, robust feature extraction from noisy signals and real-time smart monitoring. But they are only successful if they have high quality data, physical interpretability, external validation and deployment aware design. This review summarizes these problems and offers a framework to researchers and practitioners to develop more accurate, adaptive and intelligent ultrasonic measurement systems for water-based applications.

2. Physical and Measurement Foundations

The measurement of ultrasonic velocity in water is a function of the propagation of the acoustic waves, water properties, sensor geometry and signal timing. The fundamental physical value is the velocity of the propagation of the ultrasonic pressure wave in water. Ideally, this speed can be determined from the ratio of the acoustic path length to the measured travel time. In practical systems, however, the measured value will be affected by the thermodynamic state of water, the acoustic frequency, the quality of the transmission and the stability of the timing electronics. Thus, before any meaningful interpretation of the machine-learning enhancement, the physical underpinning of the velocity of sound in water needs to be determined.

2.1 Sound Velocity in Pure Water

The condition of pure water is used as a reference condition to understand the velocity of ultrasonic sound. In this instance, temperature is the most important influencing variables since the change in temperature will affect both the density and compressibility. The relationship between temperature and sound-speed is nonlinear, therefore simple linear correction is not sufficient to provide accurate calibration for the ultrasonic. The measurement of pure water is particularly critical in the laboratory environment as it enables transducers, timing circuits and signal processing procedures to be tested under controlled conditions.

The errors in time of flight measurements due to small errors in the estimation of the sound-speed can be significant. This is especially critical for short acoustic path lengths, short sampling intervals and for high accuracy calibration. Hence, pure water is commonly used as a reference liquid to test repeatability, validate measurement procedures and test the baseline behavior of ultrasonic systems. In ultrasonic calibration, the water as a reference medium is still important for it is used as a starting point before other factors such as salinity, turbidity, suspended particles, pressure variation or flowing water are taken into account (Marczak, 1997).

2.2 Sound Velocity in Natural Water and Seawater

The additional complexity of natural water and seawater is that sound velocity is affected by temperature, but also by salinity, pressure and chemical composition. In sea water, the temperature may have a significant influence close to the surface, salinity affects density and compressibility, and the pressure increases with depth. These variables are not independent and interact with each other in a nonlinear way. Consequently, formulations for the speed of sound in the ocean that consider more than just the variation of water temperature are needed for oceanographic, hydrological, and underwater acoustic applications.

Classical sound-speed equations are still important as they serve as a physical and empirical benchmark for comparing models with ML. They also specify the environmental parameters that need to be measured, estimated, or introduced into the model as inputs when constructing intelligent compensation systems. Table 1 lists the most important sound-speed formulations and reference conditions applicable to the measurement of ultrasonic velocity in water.

Table 1. Classical Sound-Speed Equations and Applicable Water Conditions

Source	Main Water Condition	Key Variables Considered	Relevance to Ultrasonic Velocity Measurement
Bilaniuk and Wong (1993)	Pure water	Temperature	Provides a high-precision reference for sound speed in pure water and supports laboratory calibration.
Del Grosso (1974)	Natural water and seawater	Temperature, salinity, pressure	Provides a detailed equation for sound speed in natural waters and is useful for oceanographic correction.
Medwin (1975)	Seawater	Temperature, salinity, depth	Offers a simplified expression suitable for practical underwater acoustic applications.
Chen and Millero (1977)	Seawater at high pressure	Temperature, salinity, pressure	Supports sound-speed estimation in deeper marine environments where pressure effects are significant.
Mackenzie (1981)	Ocean water	Temperature, salinity, depth	Provides a commonly used ocean sound-speed equation for practical acoustic and marine applications.
Coppens (1981)	Ocean and natural water	Temperature, salinity, depth	Offers a simplified expression for sound-speed estimation under realistic ocean-water conditions.
Fofonoff and Millard (1983)	Standard seawater computation	Temperature, salinity, pressure	Provides algorithmic support for computing seawater properties used in oceanographic measurement.
Lubbers and Graaff (1998)	Water and biomedical acoustic contexts	Temperature	Provides a simple sound-velocity formula relevant where temperature-based correction is required.

As observed from the table, classical equations vary in the water condition they are meant for, the range of variables and the complexity of the equations. For calibration and controlled measurements pure-water formulations are most useful. When salinity, depth or pressure variation must be considered, seawater and natural-water equations are more relevant. These equations are not only historical references for ultrasonic measurement systems, but they also form the basis of a wide variety of measurement devices. They continue to be valuable measures for determining the physical viability of ML-based predictions.

2.3 Measurement Implications for Ultrasonic Systems

These physical bases can be directly applied to ultrasonic velocity measurement. The main problem in still water is to make an accurate estimation of the acoustic velocity under known environmental conditions. The situation is more complicated in flowing water, where the ultrasonic signal is influenced by the propagation of ultrasound and the flow of the water. Transit-time systems measure the velocity based on a difference in travel time between upstream and downstream measurements, and Doppler systems measure velocity based on the frequency shifts of signals scattered from moving particles, bubbles, or interfaces. In both, the acoustic characteristics of water affect the propagation of the signal which is then analyzed by the measurement algorithm.

The difference between the acoustic velocity and the velocity of the water flow is hence important. Acoustic velocity is a characteristic of a wave in the medium. Water-flowing velocity is a characteristic of the flow of water. In many cases, ultrasonic instruments measure the velocity of the water flow by measuring the change in acoustic travel time, frequency shift, or structure of the signal. This includes the fact that the knowledge of sound-speed is of primary importance even when the ultimate measurement goal is not sound-speed, but water-flow velocity.

The relationship also points to the fact that machine learning can enhance ultrasonic measurement. Physical variables like temperature, salinity, pressure, depth, etc., can be used in conjunction with signal-derived features like arrival time, amplitude, phase, frequency content, and shape of the wave, etc., in ML models. ML-based systems can also leverage information from the environment and from signals to enhance the velocity estimation under situations where conventional corrections are incomplete. To sum up, the basic principle of ultrasonic velocity measurement in water is based on the physics of acoustic propagation, and the design of the measurement system. The physical basis is given by the classical sound-speed equations, and the modern ML methods can provide an extension of this basis for adaptive correction, nonlinear compensation and robust interpretation of complex ultrasonic signals.

3. Conventional Ultrasonic Velocity Measurement Systems

The conventional ultrasonic velocity measurement systems in water are based on the controlled transmission and reception of acoustic signals. They are either intended to measure the velocity of sound in the medium or to infer velocities of moving water from changes in signal travel time, frequency, phase and/or profile structure. Typical designs are transit-time systems, multipath or chordal-path systems, Doppler based systems and non-invasive ultrasonic metering systems. While their measurement principles are known, their performance depends on the installation geometry, water properties, signal quality, flow regime and calibration reliability.

3.1 Transit-Time Ultrasonic Systems

Transit-time ultrasonic systems measure the time it takes for the ultrasonic pulse(s) to travel between two or more transducers to estimate velocity. For still water, the measured time of flight can be used to estimate the acoustic velocity, if the path length is known. Upstream and downstream travel times are different in flowing water due to the upstream or downstream flow helping or hindering the propagation of the acoustic energy along the path. The time difference between these two transit times is then used to estimate the path averaged flow velocity. It is a non-invasive, fast and continuous measurement method, and has been widely used in hydrometry, pipeline monitoring and closed-conduit water-flow measurement.

Transit-time systems must have correct information on the acoustic path length, installation angle, timing resolution and sound speed in the water. Any of these parameters could be in error and affect the final velocity estimate. In a standardized hydrometric application, the transit-time method can be considered a formal discharge measurement method particularly when the acoustic paths are installed and calibrated within a known channel or conduct geometry (International Organization for Standardization, 2017).

3.2 Chordal-Path and Multipath Ultrasonic Measurement

Single-path transit-time systems are useful but may be limited in the case of non-uniform velocity profile. In many cases of water flow, due to wall effects, turbulence, pipe bends, stratification, or changing flow conditions, the flow velocity is not uniform throughout the pipe, channel or measurement section. To overcome this limitation, chordal-path and multipath ultrasonic systems have been developed which make use of multiple acoustic paths across the flow section. The flow estimate is obtained by integrating or weighing the path-wise samples, which are obtained from a different portion of the velocity field.

This is done to increase the reliability of the measurement as more spatial information is captured than in one path. It is particularly applicable to large conduct, hydropower channels, irrigation structures and open channel systems where flow is not often uniform. Multipath systems also add additional design requirements, however. The accuracy is dependent on the placement of each acoustic path, the weighting method and the assumed velocity distribution. Conventional ultrasonic flowmeter design (Pannell et al., 1990) thus continues to be important for integration techniques of chordal-path flowmeters.

3.3 Doppler-Based Ultrasonic Velocity Measurement

Doppler-based ultrasonic systems use the frequency change of the ultrasonic signal reflected off of moving particles, bubbles or suspended matter to calculate the velocity of the water. Doppler systems depend on acoustic scattering in the water, which is not required in transit-time systems. They can therefore be used in sediment carrying water, wastewater, natural streams and other situations where there are suspended materials. The Doppler method can also assist velocity-profile measurement as the received signal could be from various depths or spatial locations in the flow.

Due to the ability to estimate velocity distribution rather than only a path-averaged value, ultrasonic Doppler velocimetry has been widely employed to measure flow-profile. This is useful for experimental fluid mechanics, environmental flow studies and hydraulic applications where flow structure within the internal flow is important. However, its performance relies on the quality of the signal backscatter, the concentration of particles, the acoustic attenuation and the assumption that the particles scatter the signal and move with the water. Thus, measurement of water-flow structure by ultrasonic Doppler methods is a large conventional avenue of observing water-flow structure (Takeda, 1995).

3.4 Non-Invasive Ultrasonic Metering Guidelines

Non-invasive ultrasonic metering systems are appealing since they do not need to come into contact with the fluid. Clamp-on transducers, externally mounted sensors, and acoustic paths through pipe walls minimize installation disruption, and allow ultrasonic systems to be used in industrial, municipal and field applications. They are employed in situations where insertion sensors cannot be used, where pressure drop is undesirable or where continuous monitoring is desired without interrupting the flow.

Meanwhile, there are practical issues with non-invasive ultrasonic systems. The reliability of the measurements can be influenced by pipe wall material, wall thickness, acoustic coupling, transducer position, flow profile and installation conditions. The received waveform may also be diminished in quality due to signal attenuation and reflection at interfaces. Therefore, it is important to carefully install the ultrasonic non-invasive meters, select the appropriate acoustic coupling method, select the appropriate path geometry, and be aware of the limitations in use (Sanderson & Yeung, 2002).

Table 2 provides an overview of the key conventional ultrasonic measurement systems employed in water applications. It can be seen from the comparison that every method has its own principle of measurement, advantages, and disadvantages. This is crucial because the machine-learning enhancement should be tailored to the measurement architecture and not be used as a universal correction.

Table 2. Conventional Ultrasonic Velocity Measurement Systems in Water

Measurement System	Core Principle	Main Strengths	Main Limitations	Typical Water-Based Applications
Transit-time ultrasonic system	Measures upstream and downstream acoustic travel times across a known path	Non-invasive, fast response, suitable for clean water and closed conduits	Sensitive to path length, sound speed, alignment, and velocity-profile assumptions	Pipelines, hydrometry, process-water monitoring, smart metering
Chordal-path or multipath system	Uses multiple acoustic paths to sample different	Better representation of non-uniform flow,	Requires complex installation, path	Large pipes, hydropower conduits,

	regions of the flow field	improved discharge estimation	weighting, and calibration	irrigation channels, open channels
Doppler ultrasonic system	Estimates velocity from frequency shift of backscattered signals	Useful in particle-laden or turbid water, supports velocity profiling	Requires scatterers, affected by particle concentration and signal attenuation	Rivers, wastewater, sediment-laden flows, laboratory flow studies
Sound-speed profiling system	Measures or estimates vertical variation in acoustic velocity	Supports underwater acoustics, sonar correction, and marine sensing	Requires environmental correction and depth-related calibration	Oceanography, underwater navigation, acoustic communication
Clamp-on non-invasive system	Uses externally mounted transducers to transmit signals through pipe walls	No pipe cutting, no pressure loss, easy retrofitting	Affected by pipe material, coupling quality, wall thickness, and installation angle	Municipal water systems, industrial pipelines, temporary monitoring

Conventional ultrasonic systems are the technical basis for ML enhanced measurement. The main signal characteristics that ML models can be used to correct or predict are transit-time and Doppler. Multipath systems offer more spatial information, which might be used to help estimate flow-profiles from the data. The use of non-invasive systems provides practical deployment opportunities, but also adds uncertainty related to installation. Hence, the next step for smart ultrasonic measurement is to gain insight into the conventional architectures and determine where ML can be used to enhance calibration, compensation, signal interpretation, and field robustness.

4. Error Sources and Uncertainty in Water-Based Ultrasonic Measurement

The accuracy of the ultrasonic velocity measurement in water relies on the stability of the acoustic propagation, the reliability of the signal detection and the applicability of the measurement model to the actual flow condition. In the ideal situation, the ultrasonic path can be known, the wave is clear and the water medium is stable. In real applications, however, the measured signal is affected by the environmental variation, the geometry of the instruments, the flow structure and the signal degradation. These factors lead to uncertainties in the estimation of acoustic sound velocity and ultrasonic water-flow measurement.

4.1 Flow-Profile and Turbulence-Related Uncertainty

One of the big uncertainties in ultrasonic flow measuring is flow structure. Transit-time systems typically provide a measure of the path-averaged velocity, but the flow field may not be uniform throughout the cross-section of the measurement. Turbulence, pipe bends, wall friction, partial filling, stratification, secondary currents or disturbances upstream may cause velocity distribution to vary. The average velocity or discharge calculated may be biased if the assumed velocity is not representative of the actual velocity profile.

There are also issues with turbulence and the stability of signals. It may cause small changes in the local velocity and acoustic travel time, particularly if the measurement path intersects areas of unstable flow. These effects can be minimized in multipath systems by sampling multiple acoustic paths but not eliminated. Numerical and experimental investigations of the transit-time ultrasonic flowmeters indicate that flow profile and turbulence are major sources of uncertainty in the measurements, especially for an underdeveloped flow field or when path integration assumptions are not exact (Iooss et al., 2002).

4.2 Velocity-Profile Effects on Measurement Accuracy

Although it is closely related to turbulence, velocity-profile distortion is given its own consideration because it directly impacts the ability of the ultrasonic system to convert path measurements to section-averaged flow velocity. For a fully developed and symmetrical flow, a single or few acoustic paths can be used to give a good approximation. In disturbed or asymmetric flow, however, the path-wise measurement may not be representative of the entire section. This is a greater issue for large pipes, open channels and hydraulic systems where the flow profile varies over time.

Transducer position, acoustic path angle, pipe diameter and the mathematical weighting method for converting path velocity to average velocity are also factors affecting profile related errors. The ultrasonic estimate may differ from the reference value if the model is assumed to be stable with no skewness, recirculation or stratified layers in the real flow. Transit-time ultrasonic flowmeters have been studied, and it has been found that the accuracy of the measurement can be directly affected by the variation in the velocity profile, particularly when the installation conditions or hydraulic disturbances change the flow distribution (Zhang et al., 2019).

4.3 Environmental and Medium-Related Errors

There can be significant uncertainty from the water medium alone. The speed of sound in water is affected by temperature, salinity, pressure, dissolved solid matter and chemical composition. In shallow laboratory and pipeline systems, temperature variation is particularly significant and in marine and underwater systems, pressure and salinity are significant. Attenuation and scattering can be influenced by suspended particles, sediment, organic matter and turbidity. Gas bubbles can be especially disturbing, as they have a strong scattering and absorption of acoustic energy.

The propagation speed and received signal quality are affected by these environmental effects. The assumed sound speed will change if there is a small error in the temperature compensation. The suspended particles can cause the weakening or distortion of the waveform. Unstable echoes or multipath interference may be caused by bubbles. Doppler systems require suspended particles to backscatter, but too many or an uneven distribution of particles may cause the measurement to be unreliable. For this reason, it is necessary to control and verify the measurement environment and not treat the water medium as an acoustic constant.

4.4 Instrumental, Geometrical, and Signal-Level Uncertainty

Instrumental uncertainty is due to the measurement equipment and equipment set-up. Some of the most important factors are transducer alignment, acoustic path length, mounting angle, timing resolution, sampling frequency, electronic delay, coupling quality, and sensor ageing. There are also uncertainties in clamp-on systems due to pipe wall thickness, pipe wall material, acoustic coupling layer, and transducer placement. Even with stable water condition, the small geometric or electronic errors may result in systematic bias in time-of-flight or Doppler estimation.

Signal-level uncertainty is a condition where the ultrasonic waveform received is weak, distorted, noisy or hard to interpret. Low signal-to-noise ratio, ambiguous peaks, phase shift, attenuation and multipath reflections can affect time-of-flight detection. There are several potential sources of Doppler systems to be influenced by weak backscatter, broadband noise, or unstable particle distribution. Such issues are exacerbated in turbulent, bubbly, sediment-laden or acoustically complex water. When this is the case, uncertainty is not only a physical issue, it is a problem of how to interpret the signals.

The significant sources of uncertainty in the ultrasonic velocity measurement in water are summarized in **figure 1**. The framework illustrates that the error of measurement is the result of the interplay between environmental, hydrodynamic, instrumental, geometrical and signal level factors.

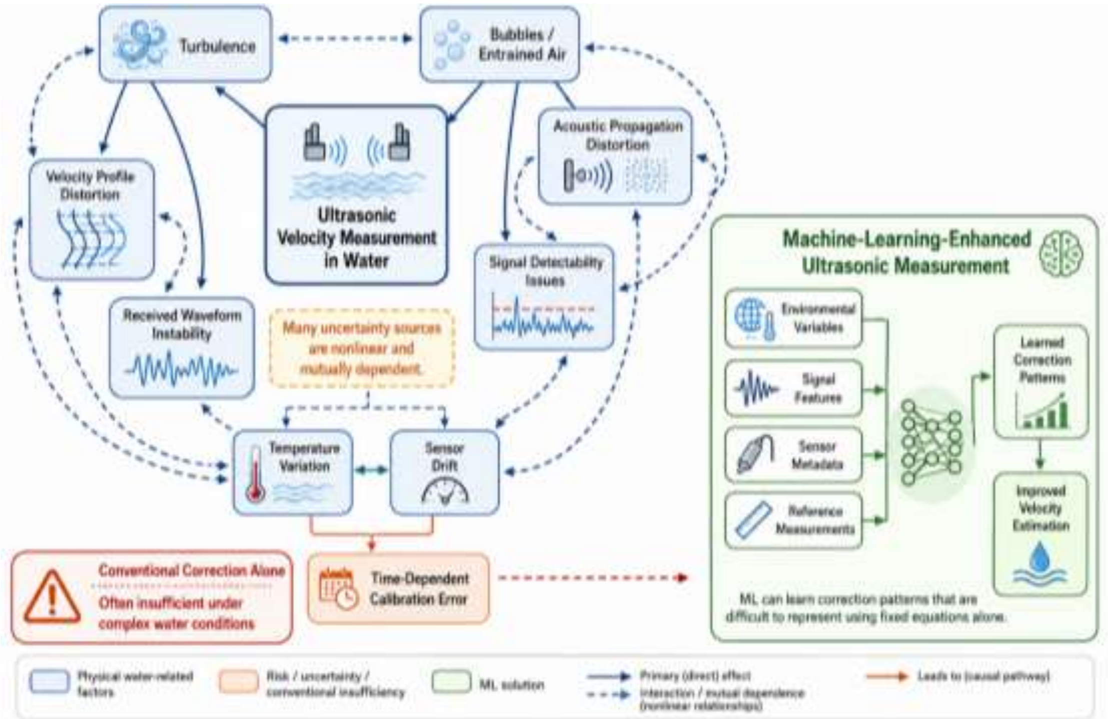

Figure 1. Error-Source Framework for Ultrasonic Velocity Measurement in Water

The figure illustrates the importance of the need for more than just conventional correction in complex water. There are also many sources of uncertainty which are nonlinear and interdependent. For instance, turbulence can change the velocity profile, as well as destabilizing the received waveform. The bubbles can alter the propagation of the acoustic signal and the detectability of the signal. The time-dependent calibration error may be due to sensor drift, in addition to the temperature variation. This complexity gives good justification for ultrasonic measurement with the help of machine learning. In addition to environmental variables, signal features, sensor metadata and reference measurements can be used as inputs to ML models to learn correction patterns that may be hard to capture with fixed equations.

5. Machine Learning Approaches for Ultrasonic Velocity Measurement

Machine learning is a computational layer to improve ultrasonic velocity measurement in water. Typical correction approaches rely on predetermined signal processing rules, calibration curves or equations. These methods are beneficial, but may not work well if the water conditions, flow structure, sensor geometry, and signal quality all vary at the same time. The ML methods can be used to learn the nonlinear relationships between ultrasonic signals, environmental variables, sensor characteristics and reference velocity values. Hence they are able to provide velocity correction, signal-quality assessment, environment compensation, sensor calibration and adaptive prediction.

5.1 ML Workflow for Ultrasonic Measurement

The first step of an ultrasonic measurement system enhanced by ML is typically signal acquisition. Time-of-flight, Doppler shift, amplitude, phase, waveform shape or frequency domain features are recorded by the system. These signal variables can be used in conjunction with temperature, salinity, pressure, flow condition, sensor spacing, pipe geometry, or sensor calibration metadata. Once the raw data is preprocessed and features are extracted, the ML model is used to learn to predict the corrected sound velocity, water-flow velocity, sound-speed profile, signal quality or measurement error, as illustrated in **Figure 2**.

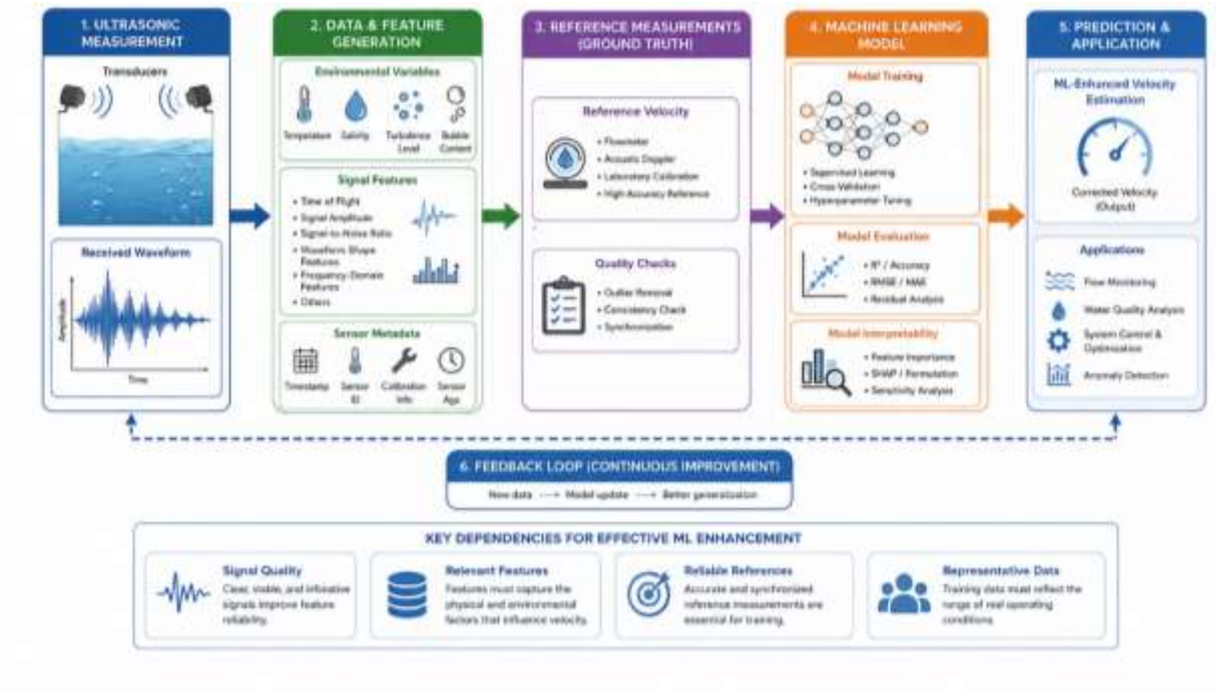

Figure 2. Machine-Learning Workflow for Ultrasonic Velocity Measurement in Water

This workflow shows that ML does not replace ultrasonic measurement. Instead, it improves how acoustic signals are interpreted under complex operating conditions.

5.2 Classical ML and Neural-Network Models

Classical ML models are applicable to moderate-sized and structured datasets. Signal and environmental features can be related to corrected velocity estimates using regression models, decision trees, random forests, support vector regression, and gradient-boosting models. Random forests are particularly interesting, as they can model nonlinear interactions between features without any single form of model being specified as a priori (Breiman, 2001).

Neural networks can further this ability by learning more flexible nonlinear relationships between the ultrasonic inputs and velocity outputs. They are helpful when there are multiple variables that interact with each other, such as time-of-flight, path geometry, flow condition, temperature, and signal quality, that are related to calibration error. The potential of data-driven correction for improving metering performance under nonlinear measurement conditions has already been demonstrated in the case of ultrasonic flow measurement based on neural networks (Luntta & Halttunen, 1999).

Moreover, support vector regression is also suitable for ultrasonic calibration since it is effective for small and medium size data sets. It can combine information of any number of acoustic paths and enhance velocity estimation of multipath ultrasonic flowmeter. This makes it useful where each path provides partial information about the actual flow field (Zhao et al., 2014).

5.3 Deep, Sequential, and Attention-Based Learning

Deep learning is applicable to ultrasonic measurement tasks with high dimensional data, like raw waveforms, spectrograms or time-frequency representations. Deep models can learn the signal patterns directly from the data, rather than relying entirely on handcrafted features. This is useful for arrival-time detection and waveform classification, denoising and velocity prediction in noisy measurement environments (LeCun et al., 2015).

For dynamic water systems, sequence-learning models are significant since the velocity of flow, the speed of sound and the response of the sensors might change over time. Long short-term memory networks can learn temporal dependencies and thus can be used for time-series prediction, adaptive calibration and sound-speed profile estimation (Hochreiter & Schmidhuber, 1997). This trend is further taken up by attention-based and transformer models, which can recognize the most informative parts of the signal, time steps, or environmental inputs within complex datasets (Vaswani et al., 2017).

In general, ML approaches vary in complexity, interpretability, amount of data required and suitability for deployment. Classical ML is applicable to structured features and small datasets. Neural networks and deep learning are more flexible but need more validation. Dynamic and spatio-temporal measurement problems can be solved using sequence and attention models. The best method of ultrasonic velocity measurement in water is not entirely data driven. It is a hybrid approach which involves acoustic principles, robust signal processing, reliable sensing, and well validated machine learning.

6. Signal Processing and Feature Engineering

6.1 Role of Signal Processing in ML-Based Measurement

In ultrasonic velocity measurement, signal processing plays a crucial role as the quality of the features extracted from the acoustic signals determines the performance of the machine-learning models. Water-based ultrasonic systems may receive a signal with noise or attenuation, phase distortion, multipath reflections, or weak echoes. Such problems impact the reliability of time of flight, Doppler shift, amplitude and frequency measurements. Thus, signal preparation is required prior to application of ML-based prediction or calibration.

6.2 Time-Domain and Frequency-Domain Features

The features that are frequently derived from ultrasonic waveforms are those in the time domain. These are such as arrival time, peak amplitude, envelope shape, zero-crossing point, pulse width and cross-correlation delay. These can be helpful in determining the acoustic travel time and to detect variations in signal structure due to flow, temperature, bubbles, or suspended particles. Frequency domain features can also be employed such as dominant frequency, bandwidth, spectral energy, attenuation pattern and phase shift. These features are useful for capturing information which may not be apparent in the time domain alone.

6.3 Feature Engineering in Multichannel Systems

In multichannel or multipath ultrasonic systems, feature engineering plays a crucial role. There can be a different view of the flow field from each acoustic path and the signal from all paths can be combined to better estimate the velocity if the information from each path is properly combined. Good estimation techniques can minimize the effect of outliers, unstable channels and distorted signals. In the multi- channel ultrasonic flowmeter system, random sampling and least-squares based strategies have been applied to enhance flow estimation in the imperfect measurement condition, which highlights the necessity of robust signal treatment prior to the final velocity estimation (Xu et al., 2022).

6.4 Integration with the ML Measurement Pipeline

Signal processing should not just be a preliminary step for ML enhanced ultrasonic measurement. It needs to be incorporated into the full-sized pipeline. The clean and informative features enhance the models' accuracy, minimize overfitting and help provide more stable prediction for varying water conditions. For simpler systems, manually engineered features might be adequate. In more sophisticated systems, raw waveforms, spectrograms, or time-frequency representations can be directly fed to deep-learning models. The objective in both is to be able to transform acoustic signals to reliable information for velocity prediction, compensation and calibration.

7. ML-Based Environmental Compensation and Calibration

One of the best arguments for using machine learning in the context of ultrasonic velocity measurement in water is to compensate for the environment. Typical correction models rely on the physical relationships between temperature, salinity, pressure, and sound speed that are known. Although these models are helpful, they may not adequately reflect the complete situation in the field where multiple variables are at play and complicated by signal noise, sensor geometry, flow instability, and variation in water column. The limitation can be overcome by learning the correction patterns using ML-based compensation from measured signals, environmental observations, and reference velocity data.

7.1 Sound-Speed Profile Estimation

In marine and underwater acoustics, the estimation of sound-speed profiles is particularly important. In such environments the vertical distribution of sound speed influences propagation of sound, sonar performance, underwater navigation, and underwater communication. Surface observations, satellite data, in situ measurements and historical oceanographic information can be used to estimate sound-speed profiles using ML model. Random-forest-based estimation has shown how environmental inputs can be used to reconstruct sound-speed profiles when direct measurements are limited (Ou, Qu, & Liu, 2022).

This process is enhanced by sensor fusion, by integrating satellite observations within situ sea-surface observations. This is helpful since no one data source can adequately describe the water column. Satellite data can be used to get wide spatial coverage, and in situ data can be used to get better local coverage. Thus, combination methods can facilitate the more accurate sound-speed estimation in different ocean environments (Ou et al., 2022). Other methods for reconstructing sound speed are nonlinear inversion techniques, which can be used to determine complex relationships between surface variables and subsurface acoustic structure, such as those using self-organizing maps (Li, Qu, & Zhou, 2021).

7.2 Multi-Source and Deep-Learning Compensation

Recent ML studies have shown a paradigm shift from single-model correction to multi-source and deep-learning based sound-speed inversion. Multi-source remote-sensing methods can combine sea-surface temperature, salinity, height and other ocean parameters to aid sound-speed prediction over wider areas (Feng et al., 2024). This ability is expanded by deep-learning frameworks that model spatio-temporal patterns in underwater sound-speed fields, critical when the sound speed varies in both space and time (Huang et al., 2023).

Satellite observation is also beneficial for ML-based underwater sound-speed estimation, as satellite-derived variables can serve as wide-area inputs to models that are trained to estimate underwater acoustic conditions (Madiligama et al., 2025). More sophisticated deep-learning models have shifted to four-dimensional prediction, which involves estimating sound-speed fields in three-dimensional space and time (Li, Qin, et al., 2026). Attention-based models further enhance the value by determining the most relevant spatial and temporal features for sound-speed profile prediction (Wang et al., 2025). Recurrent models, like bidirectional long short-term memory networks, can be used for prediction in disturbed environments such as under internal-wave conditions where the sound-speed structure varies quickly (Yin et al., 2026).

7.3 Calibration and Drift Correction

In real ultrasonic systems calibration is necessary, as the behavior of the sensor could change due to installation geometry, temperature, electronic delay, ageing of the transducers, fouling and water composition. The difference between raw ultrasonic estimates and reference measurements can be learnt by ML and can be used to support calibration. After the model is trained, it can be used to correct systematic bias, identify changes in signal quality and adjust to operating conditions other than the original calibration condition.

Drift correction is also important for long-term deployments. In field systems, the sensor response can slowly drift due to ageing of the transducers, deposits, biofouling or degradation of the sensor coupling. These may cause a static calibration curve to become unreliable. Adaptive ML models can be updated with new reference data and/or quality-control indicators. But, care should be taken when validating such models so that the system does not learn noise or reinforce biased measurements.

7.4 Compensation Strategy Summary

ML-based compensation can be applied at several points in the ultrasonic measurement chain. It may correct environmental effects before velocity estimation, improve signal interpretation during feature extraction, or adjust final velocity output after comparison with reference data. **Table 3** summarizes the main compensation and calibration strategies relevant to ML-enhanced ultrasonic velocity measurement in water.

Table 3. ML-Based Environmental Compensation and Calibration Strategies

Compensation Target	**Typical Input Variables**	**ML Role**	**Expected Measurement Benefit**
Temperature compensation	Temperature, time-of-flight, waveform features	Corrects temperature-induced sound-speed variation	Improves sound-speed and flow-velocity accuracy
Salinity and pressure compensation	Salinity, pressure, depth, surface observations	Estimates acoustic correction under marine conditions	Supports seawater and underwater measurement
Sound-speed profile estimation	Satellite data, in situ observations, ocean variables	Reconstructs vertical or spatio-temporal sound-speed fields	Improves underwater acoustic prediction
Signal-quality correction	Amplitude, SNR, phase, attenuation, waveform distortion	Detects unreliable signals and corrects biased features	Improves robustness in noisy water conditions
Sensor calibration	Raw ultrasonic velocity, reference velocity, sensor metadata	Learns correction between raw and reference measurements	Reduces systematic measurement bias
Drift correction	Long-term sensor output, environmental history, quality indicators	Tracks gradual sensor change over time	Supports long-term field deployment
Multi-sensor fusion	Ultrasonic data, temperature, conductivity, pressure, optical data	Combines complementary measurements	Improves prediction under complex water conditions

In conclusion, the use of ML for compensation and calibration enhances the reliability and accuracy of ultrasonic velocity measurement by integrating acoustic data with environmental and sensor-specific information. They are particularly valuable in locations with fluctuating water conditions, where direct measurement is challenging, or where the interactions are nonlinear and cannot be completely described by conventional equations. But compensation models must be physically plausible, externally validated and traceable to reliable reference measurements. This is critical for ML-assisted ultrasonic systems to transition from experimental modelling to field deployment.

8. Applications

The use of ultrasonic velocity measurement with the assistance of ML is applicable anywhere water-flow or acoustic-velocity estimation is needed, but where it is important to keep the estimation accurate under varying conditions. The primary applications are pipeline monitoring, industrial water systems, open channel/irrigation flow, marine sound-speed profiling, environmental monitoring and smart water infrastructure. These applications primarily benefit from the use of ML for calibration, signal interpretation, environmental compensation, and robustness in noisy and/or varying environments.

For open channel and stratified flow conditions, machine learning can be especially beneficial since the velocity distribution may be non-uniform and can be hard to describe using fixed hydraulic assumptions. Under such complex flow conditions, velocity estimation can be improved by using mobile ultrasonic systems and ML (Pu et al., 2025). **Table 4** represents the Application Domains of ML-Enhanced Ultrasonic Velocity Measurement in Water.

Table 4. Application Domains of ML-Enhanced Ultrasonic Velocity Measurement in Water

Application Domain	**Measurement Need**	**ML Enhancement Role**	**Expected Benefit**

Pipeline water-flow monitoring	Continuous flow estimation	Bias correction and signal-quality assessment	Improved metering accuracy
Industrial process water	Stable process measurement	Temperature and drift compensation	Better process control
Open-channel and irrigation flow	Non-uniform flow estimation	Flow-pattern learning and stratified correction	More reliable water management
Marine and underwater acoustics	Sound-speed profile estimation	Environmental data fusion and profile prediction	Improved acoustic system performance
Environmental monitoring	Measurement in turbid or dynamic water	Noise handling and robust feature extraction	More stable field measurement
Smart water infrastructure	Real-time connected monitoring	Edge AI and anomaly detection	Faster operational decision-making

Overall, these applications show that ML is most valuable when ultrasonic measurement is affected by variable water properties, unstable flow, sensor drift, or degraded signal quality.

9. Comparative Evaluation of Existing Approaches

9.1 Overview of Enhancement Approaches

There are several ways to improve ultrasonic velocity measurement in water, such as by using an empirical correction equation, using conventional signal processing, using classical machine learning, deep learning and physics-informed modelling. These are two different strategies with their own merits. If the water condition is known and stable, then the empirical equations will be useful. Signal processing techniques work well if the received waveform is well defined and the measurement geometry is carefully controlled. For structured data and nonlinear calibration classical ML models are useful. Raw waveform, spectrogram or time-series interpretation is more appropriate for deep learning. Physics-informed models are useful when it is important for predictions to be compatible with acoustic and fluid-mechanical principles.

9.2 Strengths and Limitations of Conventional and Data-Driven Methods

A purely empirical method is generally understandable and not so effective in complex water conditions. It does not necessarily reflect the combined effects of turbulence, bubbles, suspended particles, sensor drift and waveform distortion. Although conventional signal processing enhances the extraction of features, it is still based on predetermined rules. The advantage of ML models is that they can learn the correction pattern from the calibration data. But purely data-driven models can be less effective when they are applied in conditions do not present in the training data.

9.3 Physics-Informed Learning as a Balanced Pathway

Physics-informed learning provides a more balanced route. It is a hybrid of physical laws and data-driven estimation, which enables the model to learn from the observations but to be constrained by known governing relationships. This is particularly true of ultrasonic water measurement where the propagation of the sound and the flow characteristics are determined by physical phenomena, while the actual signals are affected by the complex field conditions. Physics-informed neural networks provide a general framework for combining governing equations with neural learning in forward and inverse problems (Raissi et al., 2019).

9.4 Relevance to Ultrasound-Related Modelling

Physics-informed methods are also helpful in ultrasound-related modelling, as they can help in inverse estimation and decrease reliance on purely empirical learning. Their importance for ultrasonic measurement is that they link measured signals, properties of the material/medium and physically meaningful predictions as illustrated in **Figure 3**. This makes them promise for future ultrasonic water systems where accuracy, interpretability, and extrapolation are important (Shukla et al., 2020).

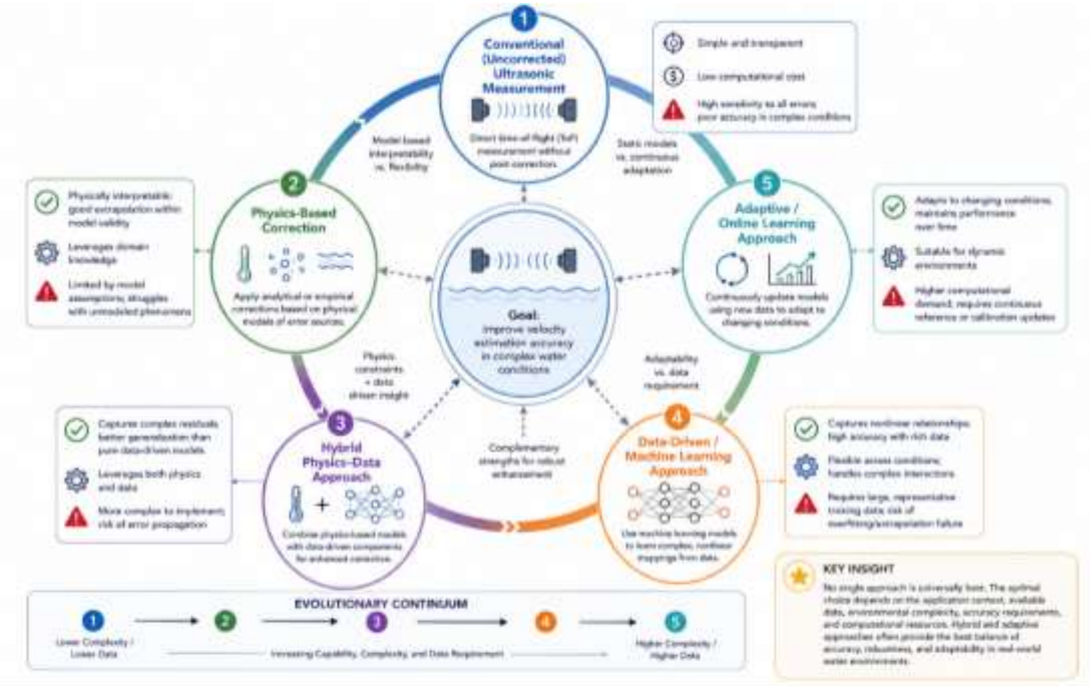

Figure 3. Comparative Taxonomy of Ultrasonic Measurement Enhancement Approaches

Generally, there is no one-size-fits-all best practice. Empirical and signal-processing techniques are still important, providing an anchoring in the physical world and stability in measurement. Adaptability and nonlinear correction are enhanced with ML methods. For the interpretation of complex signals, deep learning is beneficial. Physics-informed models are the most promising long-term trajectory, as they incorporate both acoustic theory and data-driven learning and are physically consistent.

10. Future Directions

Future studies on machine learning for the ultrasonic velocity measurement in water should focus on models which are accurate, physically consistent, interpretable, and can be deployed in real-time. While purely data-driven models can be effective in controlled datasets, they can be unreliable when the water properties, flow conditions, sensor drift and quality of the signal vary in the field.

Physics-informed learning is one of the big future directions as it can integrate the physics of acoustic propagation and prediction by neural networks. This can enhance generalization, minimize physically unrealistic outputs, and aid in inverse modelling within intricate underwater settings (Gao et al., 2026). Another priority is the estimation of full-depth and spatio-temporal sound-speed profiles. Physics-informed inversion can combine remote-sensing data, in situ measurements, and acoustic data to provide more reliable estimation of sound-speed fields as a function of depth and time (Qu et al., 2026).

Edge deployment, adaptive calibration, uncertainty estimation and multimodal sensor fusion should also be considered when developing future systems. For robustness, ultrasonic data can be used in conjunction with temperature, conductivity, pressure, turbidity, flow-depth and remote sensing data. To translate the use of ML to improve ultrasonic measurement from experimental modelling to reliable field deployment, external validation and uncertainty reporting will be critical.

11. Conclusion

The application of ultrasonic velocity measurement in water based on machine learning is a change from traditional sensing to intelligent and adaptive sensing. The traditional ultrasonic systems, such as transit-time, Doppler, multipath and sound-speed profiling systems, provide a solid technical basis. But they are influenced by temperature, salinity, pressure, turbulence, suspended particles, bubbles, sensor geometry and signal distortion. Fixed correction models are inadequate for many real-world water environments due to these conditions. Machine learning enhances ultrasonic measurement by learning the nonlinear relationships between the acoustic signals, environmental variables, sensor characteristics, and reference velocity values. It can be used for calibration correction, environmental compensation, signal-quality assessment, sound-speed-profile estimation and real-time prediction. Classical ML models can be used for structured features, deep, sequential, and attention-based models for more complex waveform and spatio-temporal data. In sum, the future of ultrasonic velocity measurement in water is in hybrid systems, which will incorporate acoustic theory, reliable instrumentation, strong signal processing, machine learning, and uncertainty evaluation. The power of ML is not to supplant existing ultrasonic concepts, but to enhance them into more precise, adaptive and deployable measurement architectures.

References

1. Baker, R. C. (2016). Flow measurement handbook: Industrial designs, operating principles, performance, and applications (2nd ed.). Cambridge University Press.
2. Bahrami, S., Alamdari, S., Farajmashaei, M., Behbahani, M., Jamshidi, S., & Bahrami, B. (2024). Application of artificial neural network to multiphase flow metering: A review. *Flow Measurement and Instrumentation, 97*, Article 102601. https://doi.org/10.1016/j .flowmeasinst.2024.102601
3. Bilaniuk, N., & Wong, G. S. K. (1993). Speed of sound in pure water as a function of temperature. *The Journal of the Acoustical Society of America, 93*(3), 1609–1612. https://doi.org/10.1121 /1.406819
4. Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32. https://doi.org/10.1023 /A:1010933404324
5. Chen, C.-T., & Millero, F. J. (1977). Speed of sound in seawater at high pressures. *The Journal of the Acoustical Society of America, 62*(5), 1129–1135. https://doi.org/10.1121/1.381646
6. Coppens, A. B. (1981). Simple equations for the speed of sound in Neptunian waters. *The Journal of the Acoustical Society of America, 69*(3), 862–863. https://doi.org/10.1121/1.385486
7. Del Grosso, V. A. (1974). New equation for the speed of sound in natural waters with comparisons to other equations. *The Journal of the Acoustical Society of America, 56*(4), 1084–1091. https://doi.org/10.1121/1.1903388
8. Feng, X., Tian, T., Zhou, M., Sun, H., Li, D., Tian, F., & Lin, R. (2024). Sound speed inversion based on multi-source ocean remote sensing observations and machine learning. *Remote Sensing, 16*(5), Article 814. https://doi.org/10.3390/rs16050814
9. Fofonoff, N. P., & Millard, R. C., Jr. (1983). *Algorithms for computation of fundamental properties of seawater* (UNESCO Technical Papers in Marine Science No. 44). UNESCO.
10. Gao, Y., Xiao, P., Xie, S., & Li, Z. (2026). Physics-informed neural networks for underwater acoustic propagation modeling: A review. *Electronics, 15*(2), Article 480. https://doi.org/10.3390/electronics15020480
11. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735
12. Huang, W., Li, D., Zhang, H., Xu, T., & Yin, F. (2023). A meta-deep-learning framework for spatio-temporal underwater SSP inversion. *Frontiers in Marine Science, 10*, Article 1146333. https://doi.org/10.3389/fmars.2023.1146333
13. International Organization for Standardization. (2017). Hydrometry: Measurement of discharge by the ultrasonic transit time (time of flight) method (ISO 6416:2017). ISO.
14. Iooss, B., Lhuillier, C., & Jeanneau, H. (2002). Numerical simulation of transit-time ultrasonic flowmeters: Uncertainties due to flow profile and fluid turbulence. *Ultrasonics, 40*(1–8), 1009–1015. https://doi.org/10.1016/S0041-624X(02)00387-6
15. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*, 436–444. https://doi.org/10.1038/nature14539
16. Li, H., Qu, K., & Zhou, J. (2021). Reconstructing sound speed profile from remote sensing data: Nonlinear inversion based on self-organizing map. *IEEE Access, 9*, 109754–109762. https://doi.org/10.1109/ACCESS.2021.3102608
17. Li, Y., Qin, J., Wu, S., Zheng, K., Niu, H., & Peng, Z. (2026). A deep learning framework for four-dimensional ocean sound speed field prediction. *The Journal of the Acoustical Society of America, 159*(2), 1400–1415. https://doi.org/10.1121/10.0042423
18. Lubbers, J., & Graaff, R. (1998). A simple and accurate formula for the sound velocity in water. *Ultrasound in Medicine & Biology, 24*(7), 1065–1068. https://doi.org/10.1016/S0301-5629(98)00091-X
19. Luntta, E., & Halttunen, J. (1999). Neural network approach to ultrasonic flow measurements. *Flow Measurement and Instrumentation, 10*(1), 35–43. https://doi.org/10.1016/S0955-5986(98)00035-1
20. Lynnworth, L. C., & Liu, Y. (2006). Ultrasonic flowmeters: Half-century progress report, 1955–2005. *Ultrasonics, 44*(Suppl. 1), e1371–e1378. https://doi.org/10.1016/j.ultras.2006.05.046
21. Mackenzie, K. V. (1981). Nine-term equation for sound speed in the oceans. *The Journal of the Acoustical Society of America, 70*(3), 807–812. https://doi.org/10.1121/1.386920
22. Madiligama, M., Zou, Z., & Zhang, L. (2025). Leveraging satellite observations and machine learning for underwater sound speed estimation. *Communications Engineering, 4*, Article 126. https://doi.org/10.1038/s44172-025-00459-6
23. Marczak, W. (1997). Water as a standard in the measurements of speed of sound in liquids. *The Journal of the Acoustical Society of America, 102*(5), 2776–2779.
24. Medwin, H. (1975). Speed of sound in water: A simple equation for realistic parameters. *The Journal of the Acoustical Society of America, 58*(6), 1318–1319. https://doi.org/10.1121 /1.380790
25. Ou, Z., Qu, K., & Liu, C. (2022). Estimation of sound speed profiles using a random forest model with satellite surface observations. *Shock and Vibration, 2022*, Article 2653791. https://doi.org/10.1155/2022/2653791
26. Ou, Z., Qu, K., Wang, Y., & Zhou, J. (2022). Estimating sound speed profile by combining satellite data with in situ sea surface observations. *Electronics, 11*(20), Article 3271. https://doi.org/10.3390/electronics11203271
27. Pannell, C. N., Evans, W. A. B., & Jackson, D. A. (1990). A new integration technique for flowmeters with chordal paths. *Flow Measurement and Instrumentation, 1*(4), 216–224. https://doi.org/10.1016/0955-5986(90)90016-Z
28. Pu, S., Liu, H., Ba, Y., Chen, Z., Yu, J., & Cui, C. (2025). Research on mobile ultrasonic stratified flow velocity measurement based on machine learning algorithms. *Frontiers in Water, 7*, Article 1590124. https://doi.org/10.3389/frwa.2025.1590124
29. Qu, K., Li, Z., Zhang, Z., & Li, G. (2026). Full-depth inversion of the sound speed profile using remote sensing parameters via a physics-informed neural network. *Remote Sensing, 18*(3), Article 438. https://doi.org/10.3390/rs18030438

30. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics, 378*, 686–707. https://doi.org/10.1016/ j.jcp.2018.10.045
31. Sanderson, M. L., & Yeung, H. (2002). Guidelines for the use of ultrasonic non-invasive metering techniques. *Flow Measurement and Instrumentation, 13*(4), 125–142. https://doi.org/10.1016/ S0955-5986(02)00043-2
32. Senthil Kumar, J., Kamaraj, A., Kalyana Sundaram, C., Shobana, G., & Kirubakaran, G. (2020). A comprehensive review on accuracy in ultrasonic flow measurement using reconfigurable systems and deep learning approaches. *AIP Advances, 10*(10), Article 105221. https://doi.org/10.1063/5.0022154
33. Shukla, K., Di Leoni, P. C., Blackshire, J., Sparkman, D., & Karniadakis, G. E. (2020). Physics-informed neural network for ultrasound nondestructive quantification of surface breaking cracks. *Journal of Nondestructive Evaluation, 39*, Article 61. https://doi.org/10.1007/s10921-020-00705-1
34. Takeda, Y. (1995). Velocity profile measurement by ultrasonic Doppler method. *Experimental Thermal and Fluid Science, 10*(4), 444–453. https://doi.org/10.1016/0894-1777(94)00124-Q
35. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. In I. Guyon, U. von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in neural information processing systems* (Vol. 30). Curran Associates.
36. Wang, S., Wu, Z., Jia, S., Zhao, D., Shang, J., Wang, M., Zhou, J., & Qin, X. (2025). A multi-spatial-scale ocean sound speed profile prediction model based on a spatio-temporal attention mechanism. *Journal of Marine Science and Engineering, 13*(4), Article 722. https://doi.org/10.3390 /jmse13040722
37. Xu, Z., Li, M., Han, Y., Li, X., & Shi, G. (2022). Robust flow estimation algorithm of multichannel ultrasonic flowmeter based on random sampling least squares. *Sensors, 22*(19), Article 7660. https://doi.org/10.3390/s22197660
38. Yin, H., Qu, K., Wang, H., & Li, G. (2026). Prediction of sound speed profiles under disturbance of strong internal solitary waves using bidirectional long short-term memory network. *Journal of Marine Science and Engineering, 14*(8), Article 735. https://doi.org/10.3390/jmse14080735
39. Zhang, H., Guo, C., & Lin, J. (2019). Effects of velocity profiles on measuring accuracy of transit-time ultrasonic flowmeter. *Applied Sciences, 9*(8), Article 1648. https://doi.org/10.3390/app9081648
40. Zhao, H., Peng, L., Takahashi, T., & Hayashi, T. (2014). Support vector regression-based data integration method for multipath ultrasonic flowmeter. *IEEE Transactions on Instrumentation and Measurement, 63*(11), 2717–2725. https://doi.org/10.1109/TIM.2014.2326276