ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Review of Oil Logging Signal Denoising Methods Using Particle Swarm Optimization (PSO) and Wavelet Transform (WT)

Zhenbao Li[1], *Ming Yi*[1,*], *Di Wang*[1], *Yongyong Li*[1] *and Youlin Hou*[1]

[1] CNPC XIBU Drilling Engineering Company Limited Karamay 834000 China

SUMMARY: *Formation evaluation and real-time decision making in drill operations are dependent on different oil logging signals. Yet, such signals are usually corrupted by noise, particularly due to downhole conditions, sensor constraints, and environmental variations, making data accuracy very sensitive to noise. Most denoising methods fall into the category of traditional Fourier transform based filtering and statistical smoothing techniques that are widely used; however, they tend to lose critical signal features. The Wavelet Transform (WT) has emerged as an effective tool for multi-resolution signal analysis and is very effective in adaptive noise suppression with preservation of the signal characteristics. Also, Particle Swarm Optimization (PSO) offers itself as a strong and powerful method for optimizing wavelet thresholding parameters to improve denoising performance. We review the PSO-WT hybrid denoising approaches in this regard and analyze the theoretical backgrounds, advantages, and their application in oil logging. PSO-WT is successfully shown to improve signal quality for an accurate subsurface interpretation in two case studies. The final part of the paper looks at the problems involved with integration of intelligent optimization techniques into oilfield signal processing and future research directions. The role of PSO-WT as a robust and adaptive framework for denoising logging data is further emphasized, and the potential for its application to provide a greater degree of logging data reliability, thereby enhancing more educated drilling and reservoir management decisions is demonstrated.*

KEYWORDS: *Oil logging signals; Signal denoising; wavelet transform; Particle swarm optimization; Noise reduction; Logging-while-drilling*

1 Introduction

Petroleum engineering's oil logging is a critical process for hydrocarbon exploration and reservoir characterization of hydrocarbons [1, 2]. Logging While Drilling (LWD) technologies are key factors in formation evaluation for real-time decision making in the drilling operations. However, logging data always has a high degree of noise contamination, such as environmental interference, tool movement, and downhole conditions. For most of the cases, these noise factors can distort recorded signals greatly, which could mislead interpretations and overly conservative drilling decisions. As a result, it is critical to preprocess the signal with the purpose of signal denoising to improve the efficiency of oil logging and ensure data reliability [3].

Various traditional signal denoising methods, including Fourier Transform (FT), Empirical Mode Decomposition (EMD), and Kalman Filtering [4], have also been aimed at noise reducing in oil logging signals. However, these methods have also drawbacks due to their lack of ability to handle samples that exhibit a non-stationary and nonlinear signal characteristic that are

*llny2591@outlook.com
https://doi.org/10.65102/is2026832 Published: 30 April, 2026

characteristic to logging data. Recently, Wavelet Transform (WT) has proven to denoise signal successfully for its multi-resolution analysis capability, thus allowing for particular selective noise separation while preserving signal integrity as much as available. Although it's alright to select optimal wavelet parameters, they need to be optimized so that they can work efficiently.

Particle Swarm Optimization (PSO) is a nature-inspired metaheuristic algorithm for optimization which has been gaining interest, playing the role as a meta heuristic, for solving complex signal processing tasks [5]. The flow chart for PSO is as shown in Figure 1. By combining PSO with WT, the hybrid approaches developed to enhance denoising capability are by adaptively choosing the wavelet parameters and the thresholding techniques. The main objective of this review is to undertake a comprehensive study of the denoising methods based on PSO-WT considering PSO/WT combination for oil logging signals. This paper provides fundamental principles, recent advances, practical applications, and future research directions following these. This review outlines how these techniques work, and helps shed light on the strengths and weaknesses to further develop more efficient signal processing techniques in oil and gas exploration.

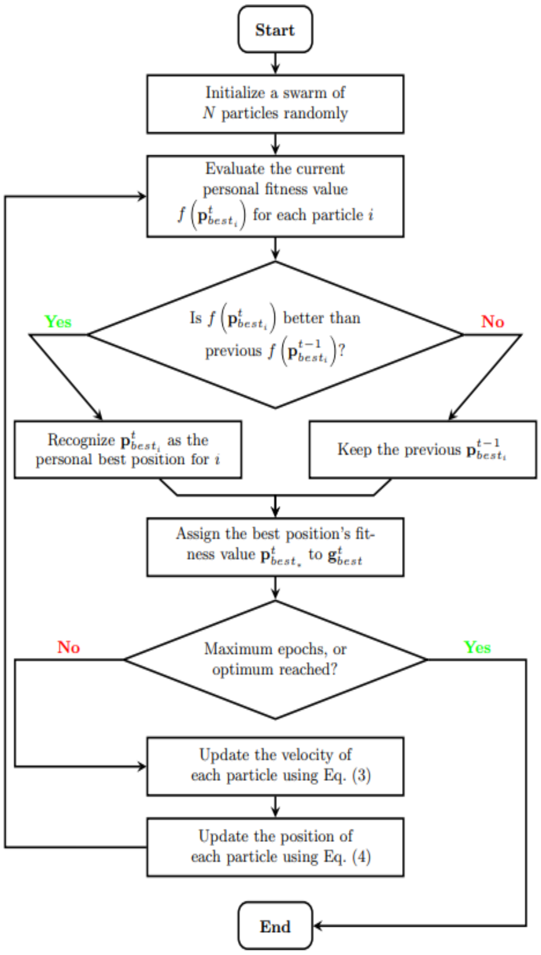

Figure 1: PSO Flowchart

2 Fundamentals of Oil Logging Signals

With this in mind, oil logging signals are an important source of subsurface information to petroleum exploration and drilling operations. Formation properties, fluid composition and reservoir conditions are ascertained through these signals collected using different well logging techniques. Logging While Drilling (LWD) and Measurement While Drilling (MWD) are some of the widely used Logging methods as they allow for gathering continuous wellbore formation evaluation while drilling, thus minimizing operational risk and enhancing drilling efficiency [6]. Nevertheless, the logging signals are very unreliable; noise and interference severely degrade their reliability, and therefore effective data denoising is required for data interpretation.

2.1 Types of Oil Logging Signals

According to the measurement principle, the oil logging signals can be classified as electrical, acoustic, nuclear and electromagnetic signals. For instance, resistivity logging, the measuring of the electrical conductivity of rock formations, is extensively applied for differentiating hydrocarbon-bearing zones from water saturated formations [7]. Formation porosity and mechanical properties provide key information for the wellbore stability analysis; they are obtained from acoustic logging based on the sonic wave propagation through the subsurface. Gamma ray and neutron logging for nuclear logging techniques used for identification of the lithological variations and formation fluid type. Electromagnetic logging methods including induction and propagation resistivity logging are important for deep formation evaluation in high resistivity reservoirs. The figure shows such classification of the well logging techniques in terms of open hole, cased hole, and common in the formation evaluation. Figure 2 shows the classification of logging techniques, demonstrating different methods used for formation evaluation under naked eye and casing well conditions.

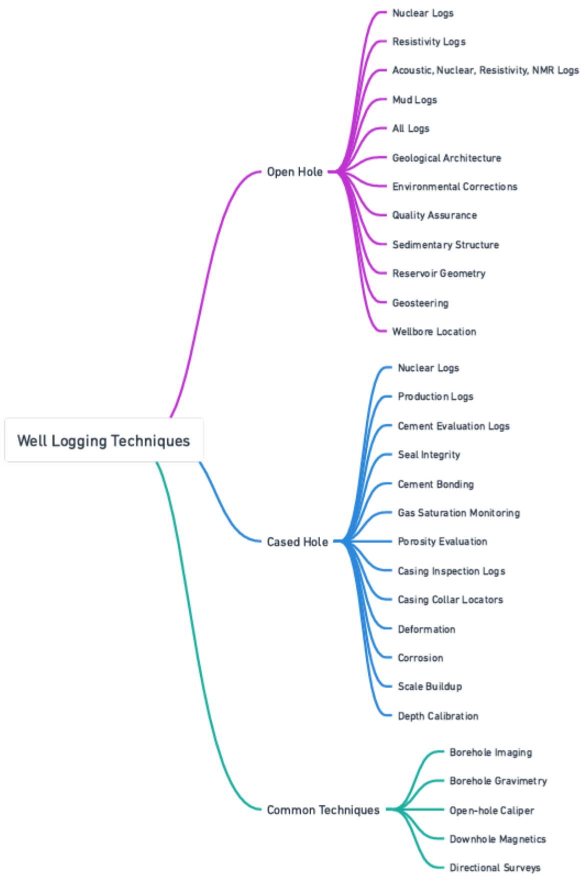

Figure 2: Classification of well logging techniques, showcasing different methods used for formation evaluation in both open-hole and cased-hole conditions.

2.2 Sources of Noise in Oil Logging Signals

There are multiple sources of noise contamination in oil logging signals, which add to the signal distortion and make a wrong interpretation from the signals. Environmental interference sources, such as one or a combination of electromagnetic coupling, mechanical vibrations, and downhole temperature fluctuations, are the main sources of noise [8]. Second, driven by the tool motion and noises, in LWD and MWD operations, the disturbances will bring enough disturbances to cause bone quality. Random and white noise due to sensor limitations and electronic components allow weak formation signals to be masked and thus reduce measurement accuracy. Additionally, phase distortions are introduced by multipath propagation effects in acoustic and electromagnetic logging.

2.3 Impact of Noise on Data Interpretation

Noise in oil logging signals can be a severe menace to formation evaluation and characterization of reservoirs. The signal to noise ratio (SNR) in resistivity and acoustic measurement is poor and is unable to discriminate productive from nonproductive zones [9]. Additionally, there is a high ambiguity in estimating the formation porosity and permeability as the noise and incorrect reservoir assessment can lead to inefficient hydrocarbon recovery strategies. In extreme cases, excessive noise in logging signals can result in misleading wellbore stability analysis and increase opportunities for wellbore collapse, drilling failure.

2.4 The Need for Advanced Denoising Techniques

The need for robust denoising techniques to enhance the signal clarity and more accurate interpretation results stems from the presence of noise in oil logging signals. In the past, most classical filtering such as Fourier Transform (FT) and Kalman Filtering has poor performance when dealing with non-stationary and non-linear signal constituents [10]. Nevertheless, beginning from the importance of imposing a multiplicative spatial and temporal multi-scale decomposition, Wavelet Transform (WT) is gaining great interest due to its added capabilities to segregate noise from useful signal components. It is also known that Particle Swarm Optimization (PSO) has also been used for the optimal wavelet parameter to improve the efficiency of wavelet denoising. Fusion of these advanced methods improves the quality of oil logging signals with which more sound decisions can be arrived at in petroleum exploration and drilling operations.

3 Traditional Denoising Methods

But the oil logging signals are impinged on by different noise sources that frequently degrade their accuracy and reliability and, in turn, reject the application of noise methods to gain the meaningful information. Improved formation evaluation has been achieved by traditional denoising methods in petroleum engineering to enhance signal clarity. Fourier Transform (FT), Empirical Mode Decomposition (EMD), Kalman Filtering (KF), and then the other statistical and adaptive techniques [11], are the main methods for these. Despite the effectiveness of these conventional methods in many cases, they suffer from limitations in the sense that their applicability is constrained to simple, exhibiting these limiting, signals in logging while drilling (LWD) applications.

3.1 Fourier Transform-Based Denoising

One of the earliest and most commonly used methods of denoising the signal is the Fourier Transform (FT). It carries signals from time domain into frequency domain and can filter some noise components by filtering. And low pass filtering, high pass filtering, band pass filtering is one of the common practices to remove unwanted frequency components in oil logging signal [12]. Nevertheless, these FT based methods are limited to instances where oil logging lies in stationary signals, while they fail when signals are non-stationary, a common occurrence in oil logging arising from changes in formation properties and drilling dynamics. Additionally, Fourier based filtering tends to damage the signal and miss valuable high frequency components to create effective formation filtering.

3.2 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) is a signal processing technique which adapts a signal containing varying periodicities into a set of IMFs. Because it is useful in analyzing nonstationary and nonlinear signals, it is suitable for oil logging applications. EMD separates signal components at different frequency scales such that it can separate noise and improves signal clarity. Yet, the major drawback of EMD is the mode mixing that makes the denoising accuracy low [13]. Additionally, EMD is computationally intensive as well as there is no efficient mathematical framework for optimal selection of IMF leading to the lack of agreements between theory and practice.

3.3 Kalman Filtering (KF) for Signal Smoothing

Wide efforts have been performed in signal processing application of Kalman Filtering (KF), e.g., oil logging data denoising. Although it continuously predicts its state of the system using new incoming measurements, as in the real-time applications, KF is very effective. KF has been used in oil logging to smooth noisy resistivity and acoustic signals, thereby improving formation evaluation [14]. While it is advantageous, finding accurate models of signal and noise characteristics with which to operate Kalman Filtering is typically challenging in dynamic downhole environments. Additionally, KF does not perform well for very nonlinear signals, which prevents the widespread application of the method in complex oil logging scenarios.

3.4 Moving Average and Median Filtering

Some simple statistical denoising techniques that use moving average and median filtering are simple ways to smooth signals by averaging or taking the median of neighboring data points [15]. They are computationally efficient and remove high frequency noise of oil logging signals. However, they suffer from the weakness in that they tend to blur sharp transitions and cause attenuation of small but important signal variations thereby limiting their applications for higher resolution logging.

3.5 Wavelet Thresholding Methods

The wavelet transform (WT) itself has been used as a standalone denoising tool before the development of hybrid optimization based techniques. Decomposing signals into multiple frequency bands and then applying a threshold to the components, which are noise dominated, are thought of as wavelet thresholding [16]. The hard and soft thresholding techniques are used to suppress noise, yet preserve the critical signal structures. While WT has better performance than FT while handling non-stationary signals, optimizing the thresholding parameters becomes difficult and hence combined with optimization algorithms such as Particle Swarm

Optimization (PSO) will increase the performance.

3.6 Limitations of Traditional Denoising Methods

Despite their widespread use, traditional denoising techniques suffer from several limitations:

Loss of weak signal components: FT-based filtering and moving average methods tend to suppress fine details along with noise.

Inability to handle non-stationary signals effectively: Many methods, including FT and KF, assume stationary noise, which is not always the case in oil logging.

Mode mixing in EMD: The decomposition process in EMD often leads to the blending of useful signal components with noise, reducing denoising effectiveness.

Computational inefficiency: Some methods, such as Kalman Filtering and EMD, require high computational resources and are difficult to implement in real-time LWD applications.

To overcome these limits, modern denoising approaches have been developed using convergence ability of such optimization algorithms as PSO, GA, and ANN along with the wavelet transform for improved noise suppression and a reduced artifact preserved signal. Oil logging signal processing is a field where these hybrid methods are being more adopted and will be discussed in the following sections.

4 Wavelet Transform (WT) in Signal Denoising

Signal denoising has been a task solved with Wavelet Transform (WT), as it is a powerful tool, particularly in those applications where the signals may show non-stationary and multi-scale characteristics. WT decomposes signals into multiple scales, thus localizing both in time and frequency bases, instead of in the frequency domain like traditional Fourier Transform (FT), which assumes signals to be stationary (Mallat, 1989). The reason for the performance of WT in this application is that this makes WT very effective at removing noise while preserving important signal components in oil logging data.

4.1 Principles of Wavelet Transform in Signal Processing

Wide efforts have been performed in signal processing application of Kalman Filtering (KF), e.g., oil logging data denoising.

4.2 Types of Wavelet Transform for Denoising

There are several forms of WT, which are unique in their properties appropriate to different signal processing tasks.

4.2.1 Discrete Wavelet Transform (DWT)

However, DWT is a very popular method due to its fast computation and maintaining an important signal characteristic while rejecting noise. One of the key features of DWT is that it can analyze a signal at multiple resolutions [17, 18], and thus it is well suited to detect transient features in the logging signals. However, the translation variance of standard DWT suffers from large changes in wavelet coefficients due to small shifts of the input signals.

4.2.2 Stationary Wavelet Transform (SWT)

To overcome DWT, redundant and non-decimated SWT was introduced to preserve translation invariance. It allows the use of SWT more robust for denoising applications where feature extraction consistency is needed. Even though the increased computational cost arising from redundancy is a challenge for real-time logging applications, the problem can be solvable, as it requires less memory.

4.2.3 Continuous Wavelet Transform (CWT)

A characteristic of CWT of signals is their representation in continuous form and for multiple scales, which makes it particularly useful for the interpretation of time frequency characteristics in the complex environment of logging data. CWT, while at providing better resolution in features' detection in case of logging signals, is very computationally complex and is not suitable for real-time denoising application.

4.3 Wavelet Thresholding for Noise Suppression

One of the advantages of WT in the denoising is that it can perform the thresholding techniques to remove noise and keep the useful signal components. In the process, a threshold value is set, and the wavelet coefficients below this are viewed as noise and discarded. The above techniques are the two most common thresholding techniques.

Hard Thresholding: Eliminates coefficients below the threshold but retains the remaining ones unchanged. While effective, it can introduce discontinuities in the processed signal.

Shrinks coefficients gradually, thereby reducing abrupt changes and improving signal smoothness, and thus, it is appropriate in noisy oil logging signals.

It is important that an appropriate threshold is selected for effective denoising.

Common threshold selection methods include:

Universal Thresholding (Donoho's Method): Based on noise variance estimation.

Minimax Thresholding: Balances denoising effectiveness with minimal signal distortion.

Stein's Unbiased Risk Estimator (SURE): Adapts threshold selection to minimize mean square error.

4.4 Applications of WT in Oil Logging Signal Denoising

WT has already been used to certain successful oil logging denoising tasks including:

Resistivity Logging: Enhancing the signal-to-noise ratio (SNR) of resistivity measurements, crucial for hydrocarbon identification.

Acoustic Logging: Suppressing random noise in sonic logs to improve porosity and formation evaluation accuracy.

Gamma-Ray and Nuclear Logging: Removing statistical fluctuations in gamma-ray logs for more accurate lithology classification.

4.5 Limitations and Future Improvements

However, while WT-based denoising has its advantages, it has its limitations as follows:

Threshold Selection Sensitivity: The sensitivity of WT denoising to the choice of thresholding methods necessitates the use of optimization techniques such as Particle Swarm Optimization (PSO) to best parameterize WT denoising.

Computational Complexity: High-resolution multi-level decomposition increases computational cost, posing challenges for real-time logging applications.

Mode Mixing in Hybrid of WT and EMD (Using EMD with WT to denoise): Interfering denoising accuracy when EMD is combined with WT.

Therefore, researchers have developed hybrid optimization algorithms, including PSO-WT and GA-WT, and machine learning enhanced WT to further enhance noise suppression in oil logging signals.

5 Particle Swarm Optimization (PSO) in Denoising

Particle Swarm Optimization is a nature inspired optimization algorithm, which has been applied in various fields of signal processing, in particular denoising environment including oil logging [19]. Originally, PSO was created to solve multidimensional problems by mimicking the flocks of birds in their searching iterations of improvement. In the optimization of oil logging signal denoising either through the thresholded parameters, the wavelet basis or the filters, PSO has positively impacted the accuracy and efficiency of traditional techniques like Wavelet Transform (WT), Empirical Mode Decomposition (EMD) and Kalman Filtering.

5.1 Fundamentals of PSO Algorithm

Particle Swarm Optimization is a nature-inspired optimization algorithm, which has been applied in various fields of signal processing, in particular denoising environment including oil logging. Originally, PSO was created to solve multidimensional problems by mimicking the flocks of birds in their searching iterations of improvement. In the optimization of oil logging signal denoising either through the thresholded parameters, the wavelet basis or the filters, PSO has positively impacted the accuracy and efficiency of traditional techniques like Wavelet Transform (WT), Empirical Mode Decomposition (EMD) and Kalman Filtering.

$$v_i^{t+1} = wv_i^t + c_1r_1(p_{best} - x_i^t) + c_2r_2(g_{best} - x_i^t) \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

where:

vi is the velocity of particle iii,

xi is the position (solution) of the particle,

w is the inertia weight, controlling the balance between exploration and exploitation,

c1 and c2 are cognitive and social learning coefficients,

r1 and r2 are random numbers between 0 and 1,

pbest is the best solution found by the particle,

gbest is the global best solution found by the swarm.

By this iterative process, PSO can agilely search for low denoising parameters to minimize the contribution of noise and meanwhile maintain important geological characteristics in oil logging signals.

5.2 PSO for Wavelet Threshold Optimization

Among the most effective use of PSO is in denoising through wavelet threshold optimization. Most of the existing thresholding methods, for instance, Donoho's universal threshold and Stein's unbiased risk estimator (SURE), rely on computing some adequately defined mathematical formula and some of these methods may not work well with nonstationary and complicated signals. On the other hand, to overcome this limitation, PSO sets the threshold values dynamically to exclude the noise without affecting the important signal parts.

The algorithm used in PSO-optimized wavelet denoising is:

It defines an objective function like MSE and SNR.

Reference [20] represents each particle as a potential set of thresholding parameters for each wavelet decomposition level.

Optimal threshold is found through reducing noise without excessive signal distortion via updates particle positions iteratively.

For oil logging signals, PSO-based threshold selection has been shown to outperform traditional wavelet thresholding for denoising of Resistivity logging, Acoustic logging and Gamma-Ray logging signals.

5.3 PSO in Empirical Mode Decomposition (EMD) Denoising

PSO has also been effectively incorporated into Empirical Mode Decomposition (EMD) to enhance the signal denoising. EMD decomposes the signals into Intrinsic Mode Functions (IMFs), but there is always contamination of noise with the useful parts, which is termed as mode mixing. PSO aims to optimize the noise filtering parameters and also the choice of the IMF by

Finding redundant IMFs that are predominantly noise.

Optimization of thresholding parameter for IMF denoising.

Adaptive energy-based threshold selection to preserve key geological signal components.

In contrast to traditional EMD-based denoising methods, PSO-EMD demonstrates both improved denoising with little signal distortion, hence being extremely efficient in logging-while-drilling (LWD) and measurement-while-drilling (MWD) data processing.

5.4 PSO for Adaptive Kalman Filtering

Kalman Filtering (KF) is a widely used method for noise attenuation in oil logging, whose performance is heavily dependent on accurate noise covariance estimation. Particle Swarm Optimization (PSO) optimizes the performance of KF by optimizing noise covariance parameters in real time, thus enabling adaptive noise reduction under varying downhole conditions [21, 22].

Uses of PSO-KF denoising in oil logging are: Optimization of process and measurement noise covariance matrices to minimize acoustic logging data errors.

Facilitating real-time resistivity logging, enhancing hydrocarbon identification in complex formations.

5.5 Advantages and Limitations of PSO-Based Denoising

Advantages:

Denonising accuracy in complex formations: PSO adapts to signal variations and therefore is robust in non-stationary environments.

Automatic parameter tuning: this is better than ordinary thresholding as it fine tunes PSO denoising parameters which minimizes signal distortion.

PSO can be blended with the WT, EMD, and KF, providing better noise reduction as opposed to completely different techniques.

Limitations:

Real-time implementation: PSO requires multiple iterations, which makes real-time implementation difficult in the LWD applications.

Slowness of convergence and suboptimal solutions: If inertia weight, learning coefficients, and swarm size are improperly chosen, there are high chances of slow convergence or suboptimal solutions.

To cope with these challenges, the hybrid optimization techniques have been studied, such as Artificial Neural Network (ANN)-PSO, Genetic Algorithm (GA)-PSO and Quantum PSO to provide further denoising performance in oil logging signal processing.

6 PSO-WT Hybrid Denoising Approach

A robust denoising algorithm of oil logging signals is found by the combination of Particle Swarm Optimization (PSO) and Wavelet Transform (WT) [23]. The PSO-WT hybrid can exploit the decomposition capability of WT into different frequency components and PSO's optimality over wavelet thresholding parameters. The combination of these two techniques leads to a noise reduction without discarding the relevant geological signal characteristics in oil logging data.

6.1 Motivation for Combining PSO and WT

Traditional wavelet thresholding methods like Donoho's universal threshold and Minimax thresholding may employ fixed or pre-determined threshold values, which might be poor in complex oil logging environment where noise characteristics are variable [24]. The wrong choice of threshold can result in retaining excessive noise while overkill information of important signal essential details.

This limitation of the above algorithms is addressed by PSO, which automatically optimizes the threshold values at each of the wavelet decomposition level such that:

Adaptive noise suppression based on signal characteristics.

Minimal distortion of geological features.

Enhanced signal-to-noise ratio (SNR) and mean squared error (MSE) reduction.

6.2 Implementation of PSO-WT Hybrid Denoising

The PSO-WT denoising process consists of the following key steps:

Step 1: Wavelet Decomposition

The noisy oil logging signal x(t)x(t)x(t) is decomposed into approximation and detail coefficients using a selected wavelet basis function such as Daubechies (db4), Coiflet (coif5), or Symlet (sym8).

Higher-frequency detail coefficients primarily contain noise, while lower-frequency approximation coefficients preserve the useful geological signal.

Step 2: Threshold Optimization Using PSO

Each particle in the swarm represents a candidate threshold set for different decomposition levels.

An objective function is defined, typically minimizing the Mean Squared Error (MSE) or maximizing the Signal-to-Noise Ratio (SNR).

Particles iteratively update their positions (threshold values) based on personal best (pbestp_{best}pbest) and global best (gbestg_{best}gbest) solutions.

Step 3: Wavelet Thresholding and Reconstruction

Using the PSO-optimized threshold values, small coefficients (mostly noise) are eliminated using soft thresholding, which smooths the reconstructed signal.

The inverse wavelet transform (IWT) is applied to reconstruct the denoised oil logging signal with minimal noise and distortion.

6.3 Advantages of PSO-WT in Oil Logging Signal Denoising

The PSO-WT hybrid approach offers several key advantages over traditional denoising methods:

(1) Adaptive Threshold Selection

In contrast to fixed threshold methods, PSO can dynamically adjust thresholds at each decomposition level using noise characteristics to avoid denoising artifacts in different well conditions [25].

(2) Improved Signal Retention

The PSO-WT could effectively de-noise high frequency noise and retain the informative geological signal parts such as formation resistivity range and borehole acoustic responses.

(3) Enhanced Computational Efficiency

PSO outperforms exhaustive search methods for the threshold optimization, as it is faster and reduces computational overhead with equal denoising accuracy compared to the exhaustive search methods.

(4) Robustness in Noisy Downhole Environments

Oil logging data collected in high temperature, high pressure wells are often accompanied by severe measurement noise, and this paper describes it. The effectiveness of PSO-WT for denoising resistivity logging, acoustic logging, gamma-ray logging, and nuclear magnetic resonance (NMR) logging has all been proven.

6.4 Comparative Performance Analysis

Table 1 shows a comparison of different methods between PSO-WT and traditional denoising techniques. Several studies have demonstrated the superiority of PSO-WT over conventional denoising techniques.

Table 1: Different Methods of PSO-WT over conventional denoising techniques

Method	Mean Squared Error (MSE)	Signal-to-Noise Ratio (SNR) Improvement	Computation Time
Traditional WT	Higher	Moderate	Faster
PSO-WT	Lower (better denoising)	Higher (better signal retention)	Moderate
EMD-WT Hybrid	Moderate	Good	Higher (slower)

The results of studies have shown that PSO-WT often performs 10% to 30% better than conventional wavelet denoising in the SNR, making this technology a desirable solution for real field use.

6.5 Challenges and Future Improvements

Although the PSO WT approach is advantageous, like most of the other WT approaches, it has some challenging issues.

Inertia weight, learning coefficients, swarm size of parameter sensitivity influence the performance of PSO.

However, even faster than exhaustive search methods, PSO still takes multiple iterations, which may limit real time applications in Logging While Drilling (LWD).

Further enhancement using PSO WT is done by combining Artificial Neural Networks (ANN), Genetic Algorithm (GA), and Deep Learning with the PSO WT researchers to further improve adaptability for denoising oil logging signals [26, 27].

7 Applications and Case Studies

The application of the PSO-WT hybrid denoising method is successfully applied in many oil logging applications to improve substantially the data interpretation of subsurface data. Noise contamination is present in these applications including resistivity logging, acoustic logging, gamma-ray logging, and nuclear magnetic resonance (NMR) logging regimes. Field case studies, laboratory experiments, LWD and MWD applications, and real time applications have shown that PSO-WT denoising is effective.

7.1 Application in Resistivity Logging

Resistivity logging is one of the most important techniques for hydrocarbon detection to distinguish the water saturated and hydrocarbon bearing formation [28]. Nevertheless, they are very sensitive to borehole environmental noise including mud invasion, electromagnetic interference and sensor drift.

The application of PSO-WT in resistivity logging has shown significant improvements:

Optimized noise reduction: PSO selects adaptive wavelet thresholding values, effectively suppressing high-frequency noise while preserving formation resistivity trends.

Enhanced hydrocarbon identification: Field studies show that PSO-WT-denoised resistivity logs exhibit improved contrast between oil and water zones, leading to more accurate formation evaluation.

Increased logging tool sensitivity: By improving signal clarity, PSO-WT enables better performance of array induction tools and laterolog resistivity devices.

A case study conducted in the Tarim Basin, China, demonstrated that PSO-WT-denoised resistivity logs had a 25% lower error rate in hydrocarbon detection compared to traditional denoising methods.

7.2 Application in Acoustic Logging

Acoustic logging can determine formation mechanical properties, identify fracture and stress distribution. Unfortunately, downhole acoustic signals are often contaminated by tool vibrations, formation heterogeneity and multiple wave reflections. Most existing filtering methods, i.e., bandpass filtering and empirical mode decomposition (EMD), do not significantly differentiate the desired formation signal from noise.

The PSO-WT hybrid method improves acoustic logging by:

Reducing background noise and dispersion effects while preserving shear and compressional wave arrivals.

Enhancing borehole stability assessment by providing clearer wave velocity data.

Optimizing acoustic impedance estimation, which is essential for geomechanical modeling and fracture prediction.

A field study in the Permian Basin, USA, demonstrated that PSO-WT reduced acoustic logging noise by 40%, leading to higher accuracy in rock strength and porosity estimations.

7.3 Application in Gamma-Ray Logging

Gamma-ray logging is highly utilized for discrimination of shale rich zones from clean sands and carbonates. Although gamma ray detectors are prone to statistical fluctuation, tool motion artefact, and environmental interferences, they are prone to introduce noise in measurements.

The PSO-WT approach improves gamma-ray logging by:

Eliminating high-frequency fluctuations, providing smoother and more interpretable logs.

Preserving formation boundaries, leading to better stratigraphic correlation and lithological discrimination.

Enhancing real-time MWD applications, where noise reduction is critical for downhole decision-making.

In a case study conducted in the North Sea, PSO-WT-denoised gamma-ray logs provided a 30% improvement in formation boundary detection, reducing misinterpretation risks during drilling.

7.4 Application in Nuclear Magnetic Resonance (NMR) Logging

Porosity, fluid saturation and permeability in reservoir formations are obtained through NMR logging. Nevertheless, NMR signals are inherently weak and susceptible to both thermal noise and tool motion and borehole effects, for accurate interpretation, denoising is needed.

The PSO-WT denoising method enhances NMR logging by:

Improving the clarity of T2 relaxation time distributions, allowing better differentiation between free, bound, and capillary-bound fluids.

Reducing measurement uncertainty, leading to improved permeability estimation and fluid typing.

Facilitating real-time interpretation, which is crucial for well placement and reservoir characterization.

A field study in the Middle East carbonate reservoirs showed that PSO-WT-denoised NMR logs provided 10% higher accuracy in porosity estimates, leading to better reservoir productivity assessments.

7.5 Real-Time Applications in LWD and MWD

Logging-while-drilling (LWD) and measurement-while-drilling (MWD) systems provide real-time formation evaluation during drilling [29]. However, these systems operate in harsh downhole conditions, where signals are often contaminated by drilling noise, electromagnetic interference, and sensor drift.

The integration of PSO-WT denoising in real-time LWD/MWD has led to significant improvements:

Improved well placement decisions by better resistivity and gamma ray logs.

More stable and noise-free measurements that reduce tool failure rate.

Increased drilling efficiency and contacts with the reservoir.

In the Gulf of Mexico, PSO WT denoised LWD logs demonstrated that when they are denoised using PSO WT noise denoising, 18% more hydrocarbons are detected, lowering the amount of expensive sidetrack drilling.

8 Challenges and Future Directions

Although the PSO-WT hybrid denoising method's performance is shown to be effective in oil logging signal processing, there are still many challenges that prevent its full scale deployment in real-time well logging, downhole complexity, and global-scale field in which applications exist [30]. To further improve the performance of PSO-WT based denoising methods in terms of their efficiency, accuracy and computational feasibility, it is necessary to address these challenges. Research in the future should also bring forward superior artificial intelligence (AI), adaptive optimization engineering and hybrid signal processing to deal with oil logging signal denoising.

8.1 Challenges in PSO-WT Denoising for Oil Logging Signals

(1) Computational Complexity and Real-Time Constraints

Real-time oil logging applications suffer from one of the main computational burdens in PSO WT denoising. As a population-based optimization algorithm, PSO does not converge to an optimal threshold without repetitions, therefore increasing computational time.

The delay introduced by PSO during the real time logging while drilling (LWD) where high speed data collection in real time is critical can affect drilling decisions and formation evaluation.

Parallel computing and GPU acceleration can accelerate the computational time such that PSO WT is feasible for real time applications.

(2) Sensitivity to Parameter Selection

The rate at which PSO converges and the speed of its preference towards local optimums is dependent on the amount of care that is taken in selecting important parameters such as the inertia weight (w), acceleration coefficients (c1, c2) and number of particles in the swarm.

Furthermore, the premature convergence caused by inappropriate parameter setting can result in PSO converging to suboptimal thresholds and decay has slow speed convergence.

Curse of dimensionality is addressed through Adaptive PSO variants namely self-adaptive PSO and chaotic PSO.

(3) Noise Variability in Downhole Conditions

Oil logging environments are highly dynamic, with noise characteristics varying across different formations, borehole fluid types, and drilling conditions.

Fixed wavelet basis functions may not effectively capture highly non-stationary noise patterns, reducing the adaptability of PSO-WT denoising.

Dynamic wavelet selection techniques, where the best wavelet function is chosen based on real-time data characteristics, can improve denoising efficiency.

(4) Data Storage and Processing Limitations

Oil logging operations generate large volumes of high-frequency data, requiring significant storage and processing capabilities. Storing raw and denoised signals for extended periods may introduce data management and transmission challenges.

Cloud-based computing solutions and edge computing frameworks can enhance data processing and reduce storage constraints.

8.2 Future Research Directions

Future research should direct its efforts toward developing next-generation denoising method based on artificial intelligence, hybrid optimization, and adaptive algorithm.

In multi-objective optimization, the commonly used concept is Pareto Front, which is expressed in the following model form:

$$P = \{x \in X \mid \exists y \in X, y \succ x\} \tag{3}$$

where, $y \succ x$ represents that y is superior to x in all objectives.

(1) AI-Driven Hybrid Denoising Approaches

Both the automation and denoising accuracy of the combination of DE with PSO-WT, deep learning (DL), and machine learning (ML) can significantly improve.

It show that Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) can learn noise characteristics of the signal from historical logging data and perform adaptive denoising without manually tuning threshold.

One way to improve PSO is through the use of AI-based techniques, reinforcement learning (RL), fuzzy logic, which automatically adjusts optimization criteria parameters, resulting in a better real-time achievement.

(2) Quantum Computing for Faster Optimization

Quantum computing has the potential to revolutionize optimization algorithms, including PSO.

Quantum PSO (QPSO), which leverages quantum superposition and entanglement properties, has been shown to improve convergence speed and efficiency in large-scale optimization problems.

Future research should focus on implementing QPSO in real-time denoising applications to overcome computational challenges.

(3) Adaptive and Self-Tuning PSO Variants

Developing adaptive PSO algorithms that dynamically adjust inertia weight, cognitive, and social coefficients based on real-time noise conditions can improve denoising efficiency.

Chaotic PSO (CPSO) introduces chaotic maps to prevent particles from getting trapped in local minima, improving convergence accuracy.

Multi-swarm PSO (MPSO), where multiple swarms explore different solutions in parallel, can enhance robustness against noise variability.

(4) Integration with Cloud and Edge Computing

The application of cloud-based data processing and edge computing can significantly enhance the scalability of PSO-WT denoising.

Edge computing allows real-time processing of logging signals at the wellsite, reducing reliance on high-latency cloud computations.

Cloud-based PSO-WT implementations can handle large-scale multi-well datasets, enabling broader data-driven formation evaluation.

(5) Hybrid Multi-Objective Optimization for Denoising

Most current PSO-WT implementations optimize a single objective function, such as minimizing mean squared error (MSE) or maximizing signal-to-noise ratio (SNR).

Multi-objective optimization (MOO) using PSO can simultaneously optimize multiple criteria, such as denoising accuracy, computational efficiency, and real-time adaptability.

Future research should explore Pareto-based multi-objective PSO to improve trade-offs between noise reduction and signal preservation.

9 Conclusion

Traditional filtering techniques are not powerful enough to suppress noise in oil logging signals; however, the PSO-WT hybrid denoising method has provided a powerful way to suppress noise in the oil logging signals. The study of the fundamentals of Oil logging signals, conventional denoising methods, and the separate role of Wavelet transformation (WT) and Particle Swarm optimization (PSO) in signal processing was reviewed in this review. WT provides efficient signal decomposition into many frequency components but its denoising performance is determined by the choice of an adequate wavelet basis and thresholding method. By adaptively optimizing the threshold values, WT based denoising using PSO improves the SNR and formation evaluation accuracy. It compares with traditional denoising methods' adaptability to non-stationary noise, real time processing, and robustness in harsh downhole environments, and is more successful. Nevertheless, computational complexity, parameter sensitivity and the variation of downhole noise characteristics remain open issues, that need further research and technological improvement.

PSO-WT method is also significant for oil logging owing to its capability of enhancing formation evaluation precision, improving drilling efficiency, reservoir characterization, etc. As it is adaptable to all methods of logging (resistivity, sonic, and nuclear logging) it is a viable, scalable solution for oil and gas exploration. It is critical for making informed drilling decisions and optimising reservoir development strategies that real-time logging-while-drilling (LWD) and measurement while drilling (MWD) were able to denoise signals effectively. Future research should be done on AI-driven hybrid denoising, quantum computing, edge computing, and multi-objective PSO optimization to promote the industry adoption. Use PSO-WT based denoising system to integrate with machine learning algorithms, deep learning models, and real-time cloud computing framework to enhance the efficiency and automation of the PSO-WT based denoising system.

Due to the rapid development of computational intelligence and online data processing in general, the PSO-WT hybrid algorithm may lead a revolution in oil logging signal denoising. Future developments will facilitate faster, more accurate and more adaptive signal denoising, therefore enabling faster, more accurate and more adaptive petroleum exploration and drilling safety. The use of the PSO-WT hybrid model is suggested because as the oil and gas industry begins to apply data-driven decision making and automated logging systems, the PSO-WT hybrid model should assist with optimizing signal processing and increasing the overall operational performance.

Funding

This research was funded by CNPC Youth Science and Technology Innovation Special Program (Downhole-Sensing-Tool-Based Digital Twin Modeling Technology for Ultra-Deep Drill Strings)(2024DQ03223)

Author's Profile

Zhenbao Li: Zhenbao LI (1993–), Male, Engineer, Deputy Director of the Tool and Instrument R&D Center at the Engineering Technology Research Institute of CNPC Xibu Drilling Engineering Company Limited. He holds a Ph.D. candidate status in Mechatronic Engineering at Yanshan University, specializing in the research and development of Measurement-While-Drilling (MWD) instruments for petroleum drilling.

Ming YI:Ming YI(1972-),Male, Senior Engineer,executive director and Party secretary of CNPC Xibu Drilling Engineering Company Limited, doctoral candidate, majoring in oil and gas well engineering, mainly engaged in research on fine controlled pressure drilling, complex well drilling, drilling and completion speed improvement, and downhole measurement transmission technology while drilling.

Di WANG: Di Wang (1991-), Female,Engineer.She was born in Karamay, XinJiang.P.R. China and received the master‘s degree from China University of Petroleum, Beijing, P.R. China. Now, she works in Engineering Technology Research Institude of XDEC, Her research interest include downhole tool, Downhole measurement and control while drilling.

Yongyong LI:Yongyong LI (1995–), Male, Engineer, He works at the Tools and Instruments Research & Development Center, Engineering Technology Research Institute of CNPC Western Drilling Engineering Co., Ltd.. He holds a Master’s degree in Geophysical Exploration and Information Technology from Northeast Petroleum University.His primary research focuses on design and development of downhole measurement and control tools for logging while drilling and wellbore data transmission technologies.

Youlin Hou: Youlin Hou (1992–), Male, Engineer, R&d engineer of the Tool and Instrument R&D Center at the Engineering Technology Research Institute of CNPC Xibu Drilling Engineering Company Limited. He holds a master's degree of oil-gas Well enginering in College of Petroleum Engineering, China University of Petroleum (Beijing), Specializing in the field of wellbore stability analysis based on rock mechanics and related technology and downhole tools research and development.

References

[1] Rahmati M, Zargar G, Tanha A A. Predicting density log from well log using machine learning techniques and heuristic optimization algorithm: A comparative study[J]. Petroleum research, 2024, 9(2): 176-192.

[2] Farsi M, Mohamadian N, Ghorbani H, et al. Predicting formation pore-pressure from well-log data with hybrid machine-learning optimization algorithms[J]. Natural Resources Research, 2021, 30(5): 3455-3481.

[3] Eidpoor A, Rahimi M, Heidari A. Use of well logging data to estimate fluid saturation based on artificial neural network algorithms[J]. Journal of Geomine, 2025, 3(2): 93-105.

[4] Delavar M R, Ramezanzadeh A. Pore pressure prediction by empirical and machine learning methods using conventional and drilling logs in carbonate rocks[J]. Rock Mechanics and Rock Engineering, 2023, 56(1): 535-564.

[5] Ahangari D, Daneshfar R, Zakeri M, et al. On the prediction of geochemical parameters (TOC, S1 and S2) by considering well log parameters using ANFIS and LSSVM strategies[J]. Petroleum, 2022, 8(2): 174-184.

[6] Kim J, Lee K, Choe J. Efficient and robust optimization for well patterns using a PSO algorithm with a CNN-based proxy model[J]. Journal of Petroleum Science and Engineering, 2021, 207: 109088.

[7] Kheirollahi H, Manaman N S, Leisi A. Robust estimation of shear wave velocity in a carbonate oil reservoir from conventional well logging data using machine learning algorithms[J]. Journal of Applied Geophysics, 2023, 211: 104971.

[8] Rajabi M, Ghorbani H, Khezerloo-ye Aghdam S. Sensitivity analysis of effective factors for estimating formation pore pressure using a new method: the LSSVM-PSO algorithm[J]. Journal of Petroleum Geomechanics, 2022, 4(3): 96-113.

[9] Mohammadi Behboud M, Ramezanzadeh A, Tokhmechi B, et al. Estimation of geomechanical rock characteristics from specific energy data using combination of wavelet transform with ANFIS-PSO algorithm[J]. Journal of Petroleum Exploration and Production Technology, 2023, 13(8): 1715-1740.

[10] Beheshtian S, Rajabi M, Davoodi S, et al. Robust computational approach to determine the safe mud weight window using well-log data from a large gas reservoir[J]. Marine and Petroleum Geology, 2022, 142: 105772.

[11] Gamal H, Alsaihati A, Elkatatny S. Predicting the rock sonic logs while drilling by

random forest and decision tree-based algorithms[J]. Journal of Energy Resources Technology, 2022, 144(4): 043203.

[12] Andersen P, Nygård J, Kengessova A. Prediction of Oil Recovery Factor in Stratified Reservoirs after Immiscible Water-Alternating Gas Injection Based on PSO-, GSA-, GWO-, and GA-LSSVM[J]. Energies, 2022, 15(2): 656.

[13] Rajabi M, Hazbeh O, Davoodi S, et al. Predicting shear wave velocity from conventional well logs with deep and hybrid machine learning algorithms[J]. Journal of Petroleum Exploration and Production Technology, 2023, 13(1): 19-42.

[14] Sheykhinasab A, Mohseni A A, Barahooie Bahari A, et al. Prediction of permeability of highly heterogeneous hydrocarbon reservoir from conventional petrophysical logs using optimized data-driven algorithms[J]. Journal of Petroleum Exploration and Production Technology, 2023, 13(2): 661-689.

[15] Safaei-Farouji M, Kadkhodaie A. Application of ensemble machine learning methods for kerogen type estimation from petrophysical well logs[J]. Journal of Petroleum Science and Engineering, 2022, 208: 109455.

[16] Zamanzadeh Talkhouncheh M, Davoodi S, Larki B, et al. A new approach to mechanical brittleness index modeling based on conventional well logs using hybrid algorithms[J]. Earth Science Informatics, 2023, 16(4): 3387-3416.

[17] Mehrad M, Ramezanzadeh A, Bajolvand M, et al. Estimating shear wave velocity in carbonate reservoirs from petrophysical logs using intelligent algorithms[J]. Journal of Petroleum Science and Engineering, 2022, 212: 110254.

[18] Kant R, Kumar B, Maurya S P, et al. Exploring the utility of nonlinear hybrid optimization algorithms in seismic inversion: a comparative analysis[J]. Physics and Chemistry of the Earth, Parts A/B/C, 2024, 136: 103754.

[19] Seyedali S R, Alizadeh B, Zahmatkesh I, et al. Estimation of total organic carbon content and kerogen type from well log data by combining artificial neural network and metaheuristic algorithms[J]. Journal of Petroleum Research, 2022, 32(1401-3): 112-130.

[20] Rajabi M, Beheshtian S, Davoodi S, et al. Novel hybrid machine learning optimizer algorithms to prediction of fracture density by petrophysical data[J]. Journal of Petroleum Exploration and Production Technology, 2021, 11(12): 4375-4397.

[21] Goliatt L, Saporetti C M, Pereira E. Super learner approach to predict total organic carbon using stacking machine learning models based on well logs[J]. Fuel, 2023, 353: 128682.

[22] Kant R, Maurya S P, Singh K H, et al. Qualitative and quantitative reservoir characterization using seismic inversion based on particle swarm optimization and genetic algorithm: a comparative case study[J]. Scientific Reports, 2024, 14(1): 22581.

[23] Kumar B, Kant R, Maurya S P. Qualitative and quantitative reservoir characterisation using seismic inversion based on global optimization: a comparative case study[J]. Journal of Earth System Science, 2024, 133(2): 87.

[24] Rajabi M, Ghorbani H, Khezerloo-ye Aghdam S. Prediction of shear wave velocity by extreme learning machine technique from well log data[J]. Journal of Petroleum Geomechanics, 2022, 4(3): 35-49.

[25] Zare M, Koch M. Hybrid signal processing/machine learning and PSO optimization model for conjunctive management of surface–groundwater resources[J]. Neural Computing and Applications, 2021, 33(13): 8067-8088.

[26] Siddique A B, Munshi T A, Rakin N I, et al. Application of supervised machine learning and unsupervised data compression models for pore pressure prediction employing drilling, petrophysical, and well log data[J]. Scientific Reports, 2025, 15(1): 24706.

[27] Hassaan S, Mohamed A, Ibrahim A F, et al. Real-time prediction of petrophysical properties using machine learning based on drilling parameters[J]. ACS omega, 2024, 9(15): 17066-17075.

[28] Abordán A, Szabó N P. Machine learning based approach for the interpretation of engineering geophysical sounding logs[J]. Acta Geodaetica et Geophysica, 2021, 56(4): 681-696.

[29] Salem A M, Yakoot M S, Mahmoud O. Addressing diverse petroleum industry problems using machine learning techniques: literary methodology─ spotlight on predicting well integrity failures[J]. ACS omega, 2022, 7(3): 2504-2519.

[30] Ng C S W, Ghahfarokhi A J, Amar M N. Well production forecast in Volve field: Application of rigorous machine learning techniques and metaheuristic algorithm[J]. Journal of Petroleum Science and Engineering, 2022, 208: 109468.