

Original article

Mother Wavelet Selection Criteria for Wavelet Transform of Acoustic Emission Signals in Rock Stress Estimation

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Abstract

Determining in situ stress is essential for a wide range of petroleum, mining and civil engineering applications. Conventional stress measurement methods are generally time-consuming and costly, which has increased interest in core-based alternatives. Among these, the acoustic emission (AE) method exploiting the Kaiser effect offers a practical and less expensive approach. AE signals can be analyzed either through parametric methods or signal processing techniques; the latter has attracted growing attention due to its capacity to extract detailed frequency and energy information from the recorded waveforms. The wavelet transform is particularly well-suited to AE signal analysis owing to its multi-resolution capability; however, the accuracy of the results depends critically on the selection of an appropriate mother wavelet. In this study, three objective criteria signal-to-noise ratio (SNR), correlation coefficient (CC) between the original and denoised signals, and energy-to-Shannon-entropy ratio were used to evaluate and rank candidate mother wavelets. Brazilian tensile tests with simultaneous AE monitoring were conducted on rock specimens. The evaluation results identified db5 and db6 as the most suitable mother wavelets for AE signal analysis in this rock type. To validate these findings, the Kaiser effect point was independently identified using continuous wavelet transform (CWT) with db5, yielding results consistent with those obtained by the parametric method. The stress estimated from the Kaiser effect point also showed good agreement with the known preloading stress, confirming the reliability of the wavelet-based approach.

1. Introduction

In recent years, nondestructive testing (NDT) methods have been widely adopted for structural health monitoring across a range of engineering materials and applications [1]. Among these, the acoustic emission (AE) technique has gained particular prominence owing to its ability to continuously detect and monitor the release of

elastic stress waves from localized sources during material deformation [2]. AE testing is well suited to capturing the progressive failure process both in laboratory specimens and under field conditions, and the use of multiple sensors enables source localization while signal processing facilitates the identification of distinct damage mechanisms [3]. Fig 1 shows extracted AE

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parameters from an AE hit signal. A well-established application of AE in rock mechanics is the estimation of in situ stress through the Kaiser effect. The Kaiser effect states that, upon reloading, a rock specimen generates no significant AE activity until the previously applied maximum stress level is exceeded, at which point activity increases markedly [4] , [5]. By exploiting this phenomenon on core samples retrieved from the field, the in situ stress can be inferred from the stress level at which AE resumes, offering a practical and cost-effective complement to conventional measurement methods. AE data may be interpreted through two broad frameworks: parametric analysis, which extracts discrete event descriptors such as amplitude, duration, count, and energy directly from the recorded waveform; and signal processing methods based on full waveform analysis [4] , [6].

The parametric approach is widely used due to its computational efficiency and capacity to handle large data volumes, but it discards a substantial portion of the waveform information. Signal processing methods, by contrast, operate on the complete waveform and are capable of resolving time–frequency content simultaneously, which is particularly valuable for non-stationary AE signals [7] , [8] . The wavelet transform has emerged as the most widely applied tool in this category, offering multi-resolution decomposition and the ability to localized transient features in both time and frequency domains [9]. Despite this utility, the accuracy of wavelet-based AE analysis depends critically on the selection of an appropriate mother wavelet, since different wavelet families including Daubechies, Symlets, and Coiflets differ in smoothness, support length, vanishing moments, and orthogonality, and these properties directly affect the fidelity of signal decomposition and noise separation [10].

Several studies have addressed systematic mother wavelet selection in related signal processing contexts: Zamorano et al. in 2022 proposed energy and correlation-based criteria for crack detection in rotating shafts [11]; Upadhyay et al. developed a wavelet selection method for voltage sag characterization [12]; Gao et al. identified a suitable mother wavelet for AE-based gas pipeline leakage monitoring [13]; Zamorano et al. subsequently applied optimal wavelet selection in wavelet packet transform (WPT) analysis for cracked railway axle detection [14]; and Chachar

et al. in 2023 selected mother wavelets for transient analysis in HVDC transmission lines [15]. While these contributions establish clear selection frameworks across engineering domains, the specific problem of mother wavelet selection for AE signals generated during rock deformation and its direct application to Kaiser effect point identification has received limited dedicated attention.

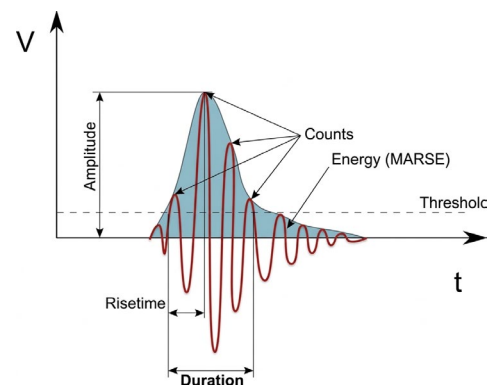


Fig. 1. Typical AE parameters from an AE signal

The present study addresses this gap by applying three objective criteria signal-to-noise ratio (SNR), correlation coefficient (CC) between the original and denoised signals, and the energy-to-Shannon-entropy ratio to evaluate and rank candidate mother wavelets for AE signals recorded during Brazilian tensile tests on Phyllite rock specimens. The most suitable wavelet identified through this process is subsequently applied in a continuous wavelet transform (CWT) analysis to locate the Kaiser effect point, and the result is compared with that obtained by the conventional parametric method, providing a cross-validation of the wavelet-based approach.

2. Theoretical Background

2.1. Wavelet Transform Techniques

The wavelet transform is a time–frequency analysis tool that, unlike the Fourier transform, uses basis functions that are simultaneously localized in both time and frequency, making it particularly well suited to the analysis of non-stationary signals such as those generated by acoustic emission. Three principal implementations are in common use: the continuous wavelet transform (CWT), the discrete

wavelet transform (DWT), and the wavelet packet transform (WPT) [16]. The basic functions termed wavelets or mother wavelets are generated from a single prototype function through scaling and translation. An N-order wavelet basis family is expressed as:

$$\psi(n) = \sum_{j=0}^{N-1} (-1)^j c_j (2n + j - N + 1) \quad (1)$$

Wherein, c_j is a coefficient. Basis functions should satisfy the following two conditions: the basis function integral is zero, i.e.

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \quad (2)$$

It is square-integral, or equivalently, and the energy is limited,

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \quad (3)$$

Equation (2) ensures that the basis function is oscillatory; Equation (3) ensures that the wavelet energy is concentrated within a finite duration.

Continuous Wavelet Transform: The CWT of a signal $f(t)$ is defined as:

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (4)$$

where a and b are the scaling and translation parameters, respectively, and ψ^* denotes the complex conjugate of ψ [5]. The CWT provides high time-frequency resolution; however, because adjacent scales and positions overlap substantially, it produces a large volume of redundant data [16], [17].

Discrete Wavelet Transform: The DWT addresses the redundancy problem by sampling the scale and translation parameters on a dyadic grid. For a mother wavelet and decomposition level j , the DWT coefficients of signal $f(t)$ are [18]:

$$\psi_{j,k}(t) = a_0^{-j/2} \psi(a_0^{-j} t - b_0 k) \quad (5)$$

$$W_f(j, k) = \int_{-\infty}^{+\infty} f(t) \psi_{j,k}^*(t) dt \quad (6)$$

Where a_0 and b_0 are constant values and k is time conversion factor. $\psi^*(j, k)$ is the complex conjugate and $W_f(j, k)$ is the coefficient of discrete wavelet in level j .

At each decomposition level the DWT produces approximation coefficients (cA), obtained by passing the signal through a low-pass filter, and detail coefficients (cD), obtained through a high-pass filter. In the standard Mallat algorithm, only

the approximation coefficients are passed to the next decomposition level, so that high-frequency detail is captured at each level but the low-frequency residual is progressively refined [18]. Because of the dyadic subsampling, the total number of coefficients equals the length of the original signal, avoiding redundancy. Wavelet Packet Transform: The WPT extends the DWT by decomposing both the approximation and the detail sub-bands at every level, producing the full binary wavelet packet tree. This allows important transient information contained in high-frequency detail nodes to be retained and examined, at the cost of greater computational effort [17]. The total number of coefficients remains equal to the signal length owing to subsampling, so redundancy is still avoided. The WPT therefore provides a flexible compromise between the high resolution of the CWT and the computational efficiency of the DWT.

2.2. Mother Wavelet and their Properties

Since many functions can satisfy the admissibility conditions in Equations (2) and (3), the choice of mother wavelet is not unique, and different wavelet families yield different decomposition results for the same signal [10]. Several families are relevant to engineering signal analysis:

Daubechies (db): The Daubechies wavelets, introduced by Ingrid Daubechies, are the canonical compactly supported orthogonal wavelets that made practical DWT implementation possible [10]. They are denoted dbN, where N is the order and simultaneously the number of vanishing moments. Daubechies wavelets have no closed-form analytical expression and are not symmetric, but their compact support and orthogonality make them highly efficient for signal decomposition and reconstruction.

Symlets (sym): The Symlets are near-symmetric modifications of the Daubechies wavelets, also proposed by Daubechies and denoted symN (N=2, 3,...,8). They retain the compactness and orthogonality of the dbN family while achieving greater phase linearity, which reduces reconstruction phase shift and helps to preserve the morphology of the analyzed signal [19].

Coiflets (coif): The Coiflet wavelets of order N are constructed so that the wavelet function has 2N vanishing moments and the associated scaling function has 2N-1 vanishing moments, with both

functions supported on an interval of length $6N-1$ [20]. This additional constraint on the scaling function improves the approximation accuracy of the wavelet expansion and makes Coiflets well suited to signals with smooth, slowly varying components.

2.3 Wavelet Selection Criteria

The performance of a wavelet-based analysis depends critically on how well the selected mother wavelet matches the signal being processed. Five properties are commonly used to guide selection. Compact support: A wavelet has compact support if $\psi(t)=0$ outside a bounded interval. Because no function can be simultaneously compactly supported in both time and frequency, compact support in the time domain is typically preferred: a narrower support provides better time-domain localisation and earlier detection of transient features, although regularity tends to decrease as support width narrows [5], [19, 20].

Orthogonality: When the wavelet basis is orthogonal, the Mallat fast algorithm can be applied, yielding an efficient and exact decomposition-reconstruction procedure without cross-term interference between sub-bands [19].

Vanishing moments: A wavelet ψ is said to have k vanishing moments if:

$$\int_{-\infty}^{\infty} f^m \psi(t) dt = 0, \quad 0 \leq m \leq k \quad (7)$$

A higher order of vanishing moments enables the wavelet to suppress smooth polynomial components of the signal, leaving transient features and singularities more prominent in the detail coefficients. However, increasing the number of vanishing moments also increases support length and computational cost [21].

Regularity: A regular (smooth, differentiable) wavelet produces well-behaved decomposition coefficients and improves the detection of signal singularities. Higher regularity is associated with a greater number of vanishing moments [21].

Symmetry: A symmetric wavelet basis yields a linear-phase filter bank, which prevents phase distortion during decomposition and reconstruction, thereby preserving the temporal morphology of the original signal [19, 22]. Table 1 summarizes these properties for the eight wavelet families considered in this study. Figure 2 illustrates the time-domain waveforms of the corresponding mother wavelets.

3. Methodology

3.1 Mother Wavelet Selection Criteria

The selection of an appropriate mother wavelet is treated here as an optimization problem in which candidate wavelets from the Daubechies, Symlet, and Coiflet families are evaluated and ranked using three objective criteria. Wavelets from families suitable only for the CWT such as Morlet and Mexican hat were excluded from consideration, as they are not compatible with the WPT decomposition employed in the evaluation [17].

Table 1. Properties of commonly used wavelet basis functions [23].

Mother wavelet	Compact support	Orthogonality	Regularity	Vanishing moments	Symmetry
Haar	✓	✓	✓	1	✓
Daubechies (db)	✓	✓	✓	N	Approx.
Biorthogonal	✓	✓	✓	N-1	Approx.
Coiflets	✓	✓	✓	2N	Approx.
Symlets	✓	✓	✓	N	Approx.
Morlet	—	✓	—	—	✓
Mexican hat	—	✓	—	—	✓
Meyer	✓	✓	—	—	✓

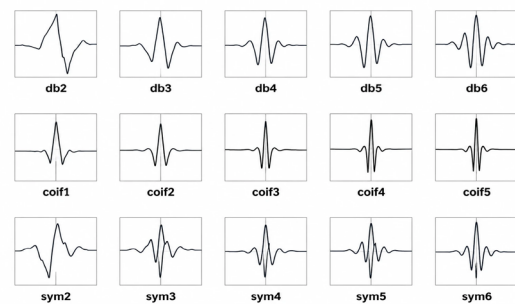


Fig. 2. Mother wavelets [23]

Correlation coefficient (CC), measures the degree of linear similarity between the original signal and its wavelet-denoised reconstruction, providing a direct indication of how faithfully a given mother wavelet preserves signal morphology during decomposition and reconstruction. Correlation coefficient (CC) which is defined between original signal and wavelet family as follows [24]:

$$CC(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_j - \bar{y})}{\left[\sum_{i=1}^n (x_i - \bar{x})^2 (y_j - \bar{y})^2 \right]^{\frac{1}{2}}} \quad (8)$$

A higher CC indicates a closer match between the denoised and original waveforms and therefore a more suitable wavelet.

Signal-to-noise ratio (SNR) is defined as the ratio of the information content of the original signal to that of the denoised signal [25]. Formally, for the i -th signal component:

$$SNR_i = \frac{A_i}{B_i} \quad (9)$$

where A_i is the i -th information measure of the original signal and B_i is the corresponding measure after wavelet-based denoising. A higher SNR indicates that the wavelet suppresses noise more effectively while retaining the true signal content [26]. Energy-to-Shannon entropy ratio, when two or more wavelets yield similar CC and SNR values, a third criterion is applied as a tie-breaker. For an optimal mother wavelet, the wavelet coefficients should concentrate energy while minimizing uncertainty; this is quantified by the ratio of energy to Shannon entropy [27, 28]. The energy of the i -th wavelet coefficient at the n -th decomposition scale is:

$$Energy(n) = \sum_{i=1}^n |C_{n,i}|^2 \quad (10)$$

The Shannon entropy of the coefficient set is defined as [29]:

$$Entropy_{Sh}(n) = -\sum_{i=1}^n P_i \log P_i \quad (11)$$

where P_i the energy-probability of the i -th coefficient:

$$P_i = \frac{|C_{n,i}|^2}{Energy(n)} \quad (12)$$

A larger energy-to-entropy ratio reflects a more compact and informative representation of the signal by the selected wavelet, indicating better alignment between the wavelet shape and the signal waveform. Prior work by Yan [30]

combined energy, Shannon entropy, and a MinMax criterion to select the optimal wavelet for vibration signal analysis, and Serrano and Fabio [31] applied minimum Shannon entropy as a selection criterion specifically for AE signals. The present study adopts the combined energy-to-Shannon-entropy ratio, evaluated over the WPT decomposed to three levels, as the distinguishing criterion when SNR and CC values are insufficiently discriminating.

3.2 Experimental Setup

Brazilian tests were conducted on rock specimens at Shahrood University of Technology. Specimens had diameters of 53–53.4 mm and a height-to-diameter ratio of 0.45–0.55, in accordance with ISRM recommended geometry for the Brazilian test. Loading was applied using a Controls C53B02 compressive loading machine. AE monitoring was performed simultaneously using a Vallen System AMSY-6 multichannel acquisition system equipped with VS900-M wideband sensors operating over a frequency range of 100–900 kHz [32]. To minimize spurious signals from background sources including environmental noise, the loading apparatus, and extraneous acoustic activity within the specimen a detection threshold of 42 dB was set on the basis of preliminary noise surveys. Additional filtering was applied in the acquisition software to suppress noise from the loading machine and ambient sources. The resulting AE dataset consisted of ten signals (S1–S10) recorded during the loading phase. These signals were used as the test corpus for the wavelet evaluation procedure.

4. Results and Discussion

Table 2 presents the SNR values obtained for 10 AE signals recorded during Brazilian testing of Phyllite rock specimens, denoised using DWT across 16 wavelet candidates from the Daubechies (db), Coiflet (coif), and Symlet (sym) families. The results reveal a clear performance hierarchy. db5 achieves the highest mean SNR of 17.902 dB, followed closely by db6 at 17.775 dB. Among the Coiflet family, coif5, coif3, and coif4 occupy the next tier, while all Symlet wavelets except sym1 perform below 16.5 dB on average. The two lowest-performing wavelets are sym2 and db2, both of which have fewer vanishing moments and shorter filter supports, rendering them less capable of capturing the sharp, transient character of AE emissions. Examining the per-signal distribution,

db5 and db6 together attain the highest SNR in 6 of the 10 signals. The peak individual values db5 reaching 21.753 dB on S9 and db6 reaching 21.961 dB on S5 illustrate that both wavelets respond well to different signal morphologies within the same rock type. The variability observed in db6 (e.g., S4 = 13.284 dB vs. S5 = 21.961 dB) suggests that while its average performance is competitive, it exhibits greater sensitivity to signal character than db5, which maintains more consistent denoising quality across all ten signals. Figure 3. Shows the bar chart of mean SNR values for the 16 candidate mother wavelets across the ten AE signals (S1–S10). This figure reveals the ranking by mean SNR for clarity. As it can see, db5 and db6 are highlighted as the top-ranked wavelets.

As shown in Table 3, the CC values across all wavelets fall within a narrow band of approximately 0.695 to 0.722. This relatively compressed range is consistent with the known characteristics of AE signals recorded during rock fracturing: their broadband, impulsive nature and high-frequency content differ substantially from more periodic machinery or partial-discharge signals, where wavelet denoising typically produces higher CC values. Nonetheless, the

relative ranking is meaningful and consistent with the SNR results. db6 achieves the highest mean CC (0.7219), with db5 at a very close second (0.7203). The coif2 through coif5 cluster occupies a narrow band from 0.7187 to 0.7196. Examining per-signal maxima, db5, db6, and coif5 each achieve the highest CC in 4 of the 10 signals, confirming that no single wavelet dominates across all signal types, but that db5 and db6 form a consistently superior pair. sym5 yields the lowest mean CC (0.7046), consistent with its poor SNR performance.

It should be noted that, given the small sample of 10 signals and the absence of a formal statistical test, differences in mean CC on the order of 0.002–0.005 should be interpreted as indicative trends rather than statistically significant distinctions. The practical conclusion that db5 and db6 outperform the remaining candidates is nonetheless supported by their consistent ranking across both criteria.

Table 2. SNR values (dB) for DWT-based denoising of 10 AE signals using 16 mother wavelets

Wavelet	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Mean
db2	15.911	14.036	14.696	16.486	13.654	14.544	14.975	16.177	10.574	11.754	14.281
db3	15.818	16.626	16.697	8.976	17.541	16.211	15.011	16.325	14.224	13.955	15.138
db4	16.824	16.733	15.305	15.279	18.502	17.056	14.543	17.452	17.224	15.189	16.411
db5	18.746	18.066	17.245	18.713	19.196	17.511	15.439	17.429	21.753	14.917	17.902
db6	20.018	19.602	19.342	13.284	21.961	17.076	16.017	16.550	18.620	15.278	17.775
coif1	15.547	15.898	15.748	13.471	15.493	16.774	14.974	12.347	16.642	12.629	14.952
coif2	17.676	17.649	16.554	15.309	19.511	16.795	15.142	16.278	17.200	15.275	16.739
coif3	17.868	17.999	15.115	17.142	18.052	16.779	15.152	17.436	18.274	16.461	17.028
coif4	17.595	18.033	15.625	17.726	18.318	17.285	15.058	15.693	18.157	16.104	16.959
coif5	17.486	18.117	16.853	17.177	18.595	17.461	15.052	16.106	18.534	16.202	17.158
sym1	18.582	16.308	11.917	16.486	16.432	17.025	14.354	17.753	16.770	17.548	16.317
sym2	15.911	14.036	14.696	8.976	13.654	14.544	14.975	10.574	16.177	11.754	13.530
sym3	15.818	16.626	16.697	15.279	17.541	16.211	15.011	14.224	16.325	13.955	15.769
sym4	16.376	15.688	14.929	14.543	17.498	16.436	14.834	13.251	17.570	13.787	15.491
sym5	18.937	16.679	16.848	11.340	16.653	16.736	15.249	14.734	17.373	13.895	15.844
sym6	17.270	16.520	15.106	16.398	17.929	16.728	15.204	14.447	18.225	15.005	16.283

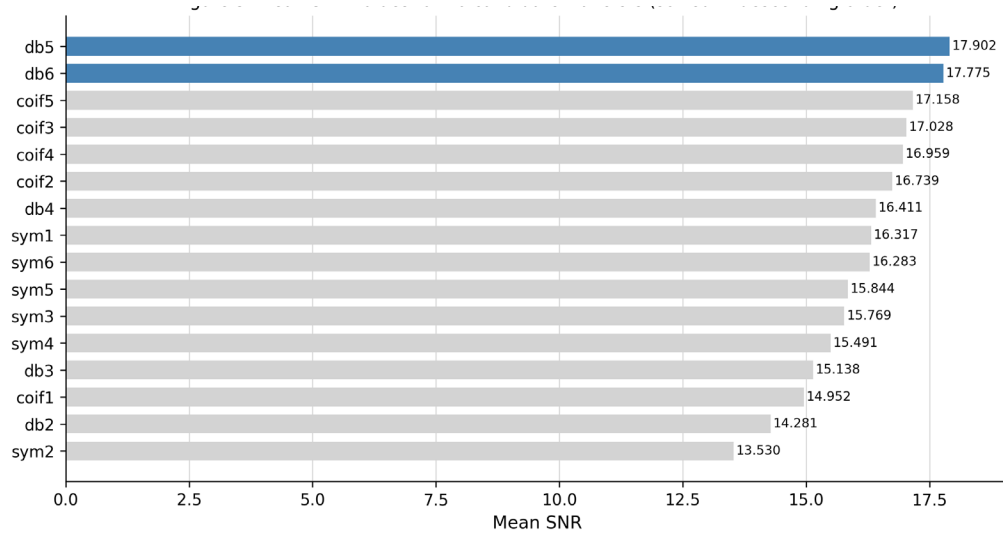


Fig. 3. Mean SNR values for the 16 candidate mother wavelets

Table 3. Correlation coefficient values between original and denoised AE signals (DWT, 16 wavelets).

Wavelet	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Mean
db2	0.6082	0.7321	0.6833	0.7014	0.7101	0.7225	0.7093	0.6846	0.7225	0.7029	0.6977
db3	0.6195	0.7308	0.6718	0.6962	0.7305	0.6686	0.7245	0.6831	0.7326	0.6955	0.6953
db4	0.6577	0.7352	0.6824	0.6999	0.7526	0.6551	0.7392	0.6913	0.7477	0.7134	0.7075
db5	0.6860	0.7427	0.6935	0.7083	0.7608	0.6716	0.7462	0.7048	0.7545	0.7348	0.7203
db6	0.6844	0.7438	0.6922	0.7144	0.7514	0.6915	0.7407	0.7121	0.7478	0.7413	0.7219
coif1	0.6984	0.7396	0.7044	0.7112	0.7455	0.6896	0.7236	0.7063	0.7295	0.7354	0.7184
coif2	0.6876	0.7421	0.6934	0.7129	0.7509	0.6877	0.7356	0.7098	0.7369	0.7394	0.7196
coif3	0.6802	0.7423	0.6878	0.7138	0.7524	0.6847	0.7404	0.7110	0.7430	0.7395	0.7195
coif4	0.6749	0.7416	0.6848	0.7141	0.7530	0.6827	0.7425	0.7113	0.7472	0.7389	0.7191
coif5	0.6709	0.7405	0.6831	0.7142	0.7533	0.6816	0.7434	0.7113	0.7501	0.7383	0.7187
sym1	0.6456	0.7237	0.7136	0.7122	0.7006	0.7658	0.6917	0.6904	0.7288	0.7284	0.7101
sym2	0.6082	0.7321	0.6833	0.7014	0.7101	0.7225	0.7093	0.6846	0.7225	0.7029	0.6977
sym3	0.6195	0.7308	0.6718	0.6962	0.7305	0.6686	0.7245	0.6831	0.7326	0.6955	0.6953
sym4	0.6794	0.7425	0.6922	0.7125	0.7420	0.7001	0.7272	0.7073	0.7288	0.7372	0.7169
sym5	0.6298	0.7419	0.6792	0.7066	0.7179	0.7217	0.7125	0.6929	0.7235	0.7203	0.7046
sym6	0.6719	0.7427	0.6847	0.7131	0.7452	0.6937	0.7331	0.7084	0.7335	0.7374	0.7164

Given the proximity of the SNR and CC results for db5, db6, and coif2, a third criterion was applied to discriminate among these top candidates: the energy-to-Shannon entropy ratio evaluated across WPT nodes up to decomposition level 3. This criterion quantifies how effectively a wavelet concentrates signal energy relative to the information spread across

the packet tree; a higher ratio at a given node indicates more efficient energy localization and less spectral mixing [28, 30]. As can be seen in Table 4, the comparison was performed between db5 and coif2, as db6 had been identified as a close competitor in the first two criteria and coif2 represented the strongest alternative from outside the Daubechies family.

Table 4. Energy-to-Shannon entropy ratio for WPT nodes (db5 vs. coif2).

Node	db5	coif2	Winner	Node	db5	coif2	Winner
cfs00	0.408163	0.408163	Tie	cfs30	0.243373	0.244444	coif2
cfs10	0.352866	0.328035	db5	cfs31	0.241647	0.238367	db5
cfs11	0.369561	0.411905	coif2	cfs32	0.270645	0.234444	db5
cfs20	0.328548	0.303933	db5	cfs33	0.264848	0.219072	db5
cfs21	0.271905	0.272385	coif2	cfs34	0.261905	0.239032	db5
cfs22	0.335352	0.316625	db5	cfs35	0.241509	0.221235	db5
cfs23	0.345849	0.332037	db5	cfs36	0.271600	0.252400	db5
				cfs37	0.262273	0.232400	db5
				Total	11	3 (+ 1 tie)	db5

The tally across all 15 nodes gives db5 a decisive advantage: 11 maxima versus 3 for coif2, with one tie at the root node. The advantage of db5 becomes especially pronounced at decomposition level 3, where db5 outperforms coif2 in six of eight nodes by margins ranging from 0.003 to 0.046. This pattern suggests that at finer frequency resolution, db5 produces packet coefficients with better energy concentration, a property that is directly relevant to AE signal analysis where frequency-band localization of crack-related emissions is desirable. coif2 achieves a higher entropy ratio only at cfs11 and cfs21 and cfs30, indicating that its higher-order smoothness is beneficial in specific sub-bands but does not translate to overall superiority. Based on this analysis, db5 is identified as the most suitable mother wavelet for the denoising and processing of AE signals recorded from the rock specimens. To evaluate the practical utility of the selected wavelet, db5 was applied to detect the Kaiser effect point using CWT on AE signals recorded from the rock specimen with a known preloading history.

Parametric method: Using conventional AE parameter analysis, a sudden increase in cumulative AE energy was observed at $t=31.3$ s in Figure 4. The corresponding stress value, read from the load diagram, was determined to be 4.3 MPa. Figure 3 illustrate load diagram and cumulative AE energy versus time, showing the abrupt increase at $t=31.3$ s. $t = 31.3$ s. **Wavelet method:** CWT with the db5 wavelet was applied to the same signal. Peak frequency was monitored as a function of time.

An increase in high-frequency activity indicative of the onset of new crack formation associated with the Kaiser effect was first detected at approximately $t \approx 31.4$ s (Figure 5). Figure 5 shows Peak frequency values derived from CWT with db5, showing onset of elevated high-frequency content at $t \approx 31.4$ s.

Stress estimated from the wavelet method is in good agreement with the preloading stress applied to the specimen. This result demonstrates that db5 is capable of resolving the time-frequency signature of the Kaiser effect point in rock AE signals; the wavelet-based approach provides a signal-level confirmation of the parametric result, reducing reliance on threshold-dependent parameter counting; the temporal precision of the CWT-db5 method is sufficient for practical in-situ stress estimation via the Kaiser effect.

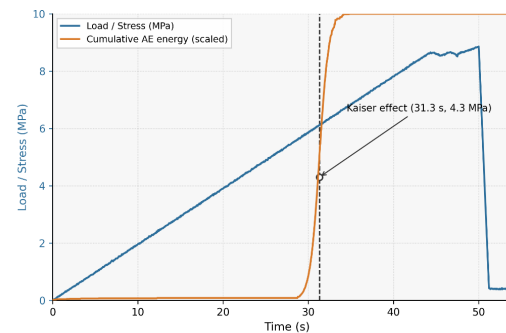


Fig. 4. load diagram and cumulative AE energy versus time from a Brazilian test

The three evaluation criteria produce a consistent and mutually reinforcing ranking. Table 5 summarizes the final comparison.

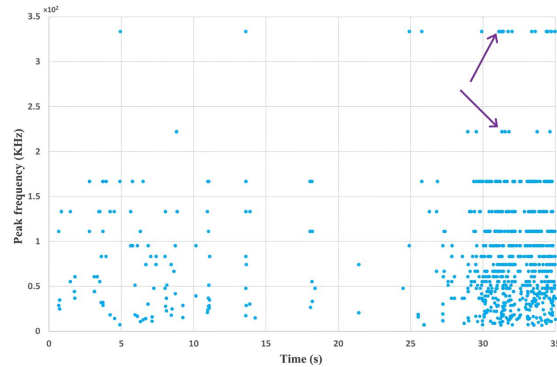


Fig. 5. Peak frequency of AE signals vs time from a Brazilian test

Table 5. Summary of wavelet performance across all three criteria.

Wavelet	Mean SNR (dB)	SNR Rank	Mean CC	CC Rank	Entropy Maxima (WPT)	Overall
db5	17.902	1	0.7203	2	11 / 15	Best
db6	17.775	2	0.7219	1	—	Runner-up
coif2	16.739	6	0.7196	3	3 / 15	—
coif3	17.028	4	0.7195	4	—	—
coif5	17.158	3	0.7187	5	—	—
sym1	16.317	8	0.7101	7	—	—

According to the obtained results, db5 ranks first in SNR and second in CC, and achieves 11 of 15 possible energy-entropy maxima in the WPT comparison. db6 is the second-best performer overall, achieving the highest mean CC and the second-highest mean SNR, and would be a viable alternative in applications where CC is the primary concern. The consistency of db5 across all three independent criteria and across all ten signal instances makes it the most robust choice for AE signal processing in rock mechanics applications of this type. The strong performance of higher-order Daubechies wavelets (db5, db6) over their lower-order counterparts (db2, db3) is consistent with the known relationship between vanishing moments and the ability to represent smooth signal components compactly [17, 24]. AE signals from brittle rock fracture, while transient and broadband, contain smooth amplitude envelopes at the macro-scale; wavelets with insufficient vanishing moments introduce oscillatory artefacts in the reconstructed signal that reduce both SNR and CC. The Coiflet family's competitive performance in the CC

metric reflects the additional regularity constraint built into coiflet design [28], but this advantage does not extend to energy localization in the WPT tree, where db5's asymmetric filter structure proves more efficient.

5. Conclusion

This study evaluated three criteria signal-to-noise ratio (SNR), correlation coefficient (CC), and energy-to-Shannon entropy ratio to identify the most suitable mother wavelet for analyzing acoustic emission (AE) signals recorded during Brazilian disc testing of the rock samples. The following conclusions are drawn:

1. Among the sixteen candidate wavelets from the Daubechies, Symlet, and Coiflet families, db5 and db6 achieved the highest mean SNR values, consistently outperforming other candidates across the majority of test signals.
2. db6 and db5 again ranked highest, with mean CC values of 0.7219 and 0.7203, respectively. The narrow range of mean CC values across all wavelets indicates that differences in reconstruction fidelity, while consistent, are modest in absolute terms.
3. Given the close performance of db5 and coif2 under the SNR and CC criteria, a further comparison was conducted using wavelet packet transform (WPT) decomposition to three levels. db5 yielded higher energy-to-Shannon entropy ratios in 11 of 15 nodes, confirming its superiority over coif2 for this dataset.
4. The CWT-based Kaiser effect point detection using the db5 wavelet identified the Kaiser effect at approximately 31.4 s, compared with 31.3 s obtained by the parametric method a difference of only 0.1 s. The stress level read from the load–time curve at that point was consistent with the expected preloading level, supporting the reliability of the wavelet-based detection approach.
5. The Kaiser effect point identified by CWT using the db5 wavelet reflected in y the parametric method, supporting the reliability of the wavelet-based approach for in-situ stress estimation.
6. The results underscore the importance of systematic mother wavelet selection in AE signal analysis. The three-criterion framework applied here is not specific to rock mechanics

and may be adapted to AE monitoring in other engineering materials and structural health monitoring applications.

6. References

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