DOI: https://doi.org/10.36910/6775-2524-0560-2025-61-39
УДК 621.396.96:519.876.5
Tulenko Igor, PhD student
https://orcid.org/0009-0007-2847-483X
Shevchenko Oleksii, PhD student
https://orcid.org/0000-0002-8321-3583
Ukrainian State University of Railway Transport, Kharkiv, Ukraine

ENTROPY-BASED EVALUATION METHOD OF SIGNAL ENSEMBLES USING LPT-T PERMUTATIONS AND MARKOV MODELS

Tulenko I., Shevchenko O. Entropy-Based Evaluation Method of Signal Ensembles Using LPT-τ Permutations and Markov Models. The article proposes an entropy-oriented method for comprehensive assessment of the structural order of signal ensembles optimized by time domain permutations. The method is based on the integration of multiscale entropy indicators, namely permutation entropy, sample entropy and fuzzy entropy, into a unified ordering criterion that enables a quantitative evaluation of the relationship between entropy-based complexity, correlation properties and the stability of signal ensembles under complex interference conditions. To evaluate the effectiveness of the proposed entropy-oriented method, experimental modeling was carried out for two approaches to time segment permutations: the deterministic LPT tau permutation method (LPT-TP) and the forecast oriented method based on Markov models. For both approaches, a multiscale entropy analysis was performed, covering the study of signal dynamics at different time scales and the evaluation of the influence of signal-to-noise ratio variations over a wide range of levels. This made it possible to analyze how changes in transmission energy conditions affect the entropy-based complexity and structural order of signal ensembles. A comparative analysis of permutation-based approaches showed that the application of LPT tau permutations increases structural order and reduces entropy measures by an average of 12–18%, whereas the Markov based permutation method demonstrates a smoother but more stable entropy reduction of 8–15%, accompanied by a 35–40% decrease in the mean mutual correlation. The obtained results confirm the efficiency of the proposed entropy-oriented method and the feasibility of its application for assessing the interference immunity, dynamic stability and structural consistency of signal ensembles in cognitive telecommunication networks.
Keywords: telecommunication networks, cognition, signal ensembles, time domain, entropy, multiscale analysis, correlation, interference immunity, uncertainty, optimization, signal-to-noise ratio (SNR).

Туленко І. М., Шевченко О. О. Метод ентропійної оцінки ансамблів сигналів на основі LPT-τ перестановок та марківських моделей. У статті запропоновано ентропійно-орієнтований метод комплексної оцінки структурної впорядкованості ансамблів сигналів, оптимізованих перестановками у часовій області. Метод базується на інтеграції багатомасштабних ентропійних показників, а саме: перестановочної ентропії, ентропії вибірки та нечіткої ентропії у єдиний критерій впорядкованості, що дозволяє кількісно оцінювати взаємозв'язок між ентропійною складністю, кореляційними властивостями та стійкістю ансамблів сигналів у складних завадових умовах. Для оцінки ефективності запропонованого ентропійно-орієнтованого методу проведено експериментальне моделювання двох підходів до часових перестановок: детермінованого методу ЛПτ-перестановок (LPT-TP) та прогнозно-орієнтованого методу на основі марковських моделей. Для обох підходів виконано багатомасштабний ентропійний аналіз, який охоплює дослідження динаміки сигналів на різних часових масштабах та оцінку впливу співвідношення сигнал/завади у широкому діапазоні рівнів. Це дало змогу проаналізувати, як зміна енергетичних умов передачі впливає на ентропійну складність і структурну впорядкованість ансамблів сигналів. Порівняльний аналіз методів перестановок ансамблів сигналів показав, що застосування ЛПτ-перестановок забезпечує підвищення структурної впорядкованості та зниження ентропійних показників у середньому на 12–18 %, тоді як метод перестановок на основі марківських моделей доводить плавніше, але стабільніше зменшення ентропії на 8–15 % при одночасному зниженні середньої взаємної кореляції у діапазоні 35–40 %. Отримані результати підтверджують ефективність запропонованого ентропійно-орієнтованого методу та доцільність його використання для оцінки завадостійкості, динамічної стабільності та структурної узгодженості ансамблів сигналів у когнітивних телекомунікаційних мережах.
Ключові слова: телекомунікаційні мережі, когнітивність, ансамблі сигналів, часова область, ентропія, багатомасштабний аналіз, кореляція, завадостійкість, невизначеність, оптимізація, сигнал-шум (SNR).

Statement of a scientific problem. Modern telecommunication networks, especially cognitive radio networks, operate under conditions of high spectral dynamics and dense frequency resource occupancy.

To ensure interference immunity, reliable data transmission, and efficient operation of multiple access systems, it is necessary to form ensembles of complex signals with controlled correlation properties, high structural order, and balanced energy distribution.

For this purpose, in the authors' previous studies, methods based on permutations of time intervals were proposed to optimize ensembles of complex signals in the time domain.

1. LPT-τ permutation method (LPT-TP). This method uses low-discrepancy lattice sequences with a *τ*-shift for deterministic control of the time structure, providing the lowest values of peak and integrated sidelobes (PSL/ISL) and the largest ensemble size.

2. Forecast-oriented method based on Markov models (Markov-forecast). This approach ensures a predictive selection of permutations to minimize the risk of transitions to high-correlation states by controlling ensemble dynamics through the uncertainty coefficient β and the transition entropy $U(\pi_i)$.

A comparative analysis of these methods is presented in Table 1.

Table 1 – Comparative analysis of optimization methods

Criterion	LPT-τ permutation method (LPT-TP)	Markov-based permutation method
Main mechanism	Deterministic time restructuring based on low-discrepancy τ-sequences.	Forecast-oriented permutation selection based on Markov transition probabilities.
Optimization goal	Minimization of correlation (PSL/ISL) and maximization of ensemble size ($S_{complex}$)	Minimization of the predicted correlation level $E[\rho_{t+1}]$ and control of transition stability.
Key control parameter	Shift parameter τ^*	Uncertainty coefficient β
Relation to entropy	Entropy measures (PE, SampEn, FuzzyEn) are used for post-analysis of structural complexity	Transition entropy $U(\pi_i)$ is used as a control term that penalizes instability within the optimization criterion $K(\pi_i)$

The efficiency of the considered optimization methods has been confirmed by a decrease in mutual correlation and an increase in the ensemble volume, as evaluated using correlation, energy, and spectral criteria. Nevertheless, these methods do not provide a complete multiscale quantitative description of the internal structural complexity and ordering of signals. Despite substantial progress achieved through correlation–energy analysis, there is still no unified criterion that consistently captures the relationship between dynamic order, entropy-based complexity, and the stability of signal ensembles under stochastic interference.

This highlights the need for a comprehensive approach to assessing the structural stability of signal ensembles. The proposed concept relies on integrating various entropy metrics, including permutation entropy (PE), fuzzy entropy (FuzzyEn), and sample entropy (SampEn), into a single optimization criterion. Such an approach links temporal ordering parameters with informational entropy characteristics, providing a quantitative measure of ensemble complexity and resilience under interference conditions.

Research analysis. Despite significant progress in digital signal processing research, constructing balanced ensembles of complex signals with a minimal level of mutual correlation remains one of the most challenging problems in modern optimization theory. The review of current approaches [1–15] encompasses methods of entropy analysis, multiscale modeling, and structural assessment of time-series complexity.

Foundational studies [1, 3, 6] introduced approaches to complexity estimation based on permutation entropy (PE) and multiscale entropy (MSE), which made it possible to analyze nonlinear dynamics of multichannel and non-stationary signals. Further development of this concept was presented in works [2, 12, 14], where multivariate and weighted entropy measures were proposed, extending the applicability of entropy analysis to more complex temporal structures.

Research studies [4, 13] introduced the concept of fuzzy entropy (FuzzyEn), while [13] presented dispersion entropy (DispEn), both providing more robust complexity estimates in the presence of noise. Works [7, 9] demonstrated the effectiveness of multiscale permutation entropy (MPE) for detecting structural changes and dynamic transitions in signals of physical processes.

The approach proposed in [8] was the first to extend the use of permutation entropy to graph-based signals, opening up possibilities for a comprehensive analysis of interrelations within network structures.

A separate group of studies focuses on modeling complex systems using Markov processes [5, 15], where state entropy is employed as a quantitative measure of uncertainty and transition stability.

In studies [10, 11], a distinct direction was formed, applying frequency and time-domain permutations to create signal ensembles with controlled correlation properties. Their results confirmed the effectiveness of deterministic permutations in improving ensemble scalability and reducing mutual correlation; however, they did not address the quantitative assessment of structural order through entropy metrics.

Therefore, the literature analysis indicates that modern entropy-based approaches effectively describe the complexity of temporal structures but remain unintegrated with deterministic optimization methods for signal ensembles. The absence of a unified criterion that combines entropy-based order measures with correlation balance parameters determines the need to develop a comprehensive method for assessing the structural stability of signal ensembles optimized by time-domain permutations.

The purpose of the work. The purpose of the study is to substantiate and develop a method for comprehensive evaluation of the structural order of complex signal ensembles optimized by deterministic time-domain permutation techniques, based on extended multiscale entropy analysis, in order to enhance interference immunity and dynamic stability in cognitive telecommunication networks.

Presentation of the main material and substantiation of the obtained research results. For the purpose of experimental verification and validation of the proposed methods for optimizing signal ensembles in the time domain, a sequential analysis of two approaches was conducted: the deterministic LPT-τ permutation method (LPT-TP) and the forecast-oriented method based on Markov models (Markov-forecast).

The first method provides the formation of structurally ordered ensembles through deterministic selection of time permutations based on low-discrepancy lattice τ-sequences, while the second focuses on predicting state transitions within the ensemble and reducing the risk of correlation instability.

To ensure a fair comparison between the methods, the efficiency of the baseline deterministic LPT-TP approach was first validated.

The formation of the signal ensemble in the time domain is performed using deterministic permutations of segments defined by the shift parameter τ.

Optimization is carried out according to the integral criterion:

$$K(\tau) = \alpha\bar{\rho}(\tau) + \beta Var[E(\tau)] + \lambda\|\Delta S_t(\tau)\|^2, \quad (1)$$

where $\bar{\rho}(\tau)$ is the average mutual correlation coefficient of the signals within the ensemble; $Var[E(\tau)]$ represents the variance of the energy distribution; $\|\Delta S_t(\tau)\|^2$ denotes the measure of structural–temporal variation of the signal; α, β, λ are weighting coefficients used to ensure the balance of the criterion.

The optimal parameter $\tau*$ is determined by the condition of minimizing the integral criterion:

$$\tau^* = arg \min_{\tau \in A} K(\tau). \quad (2)$$

After determining $\tau*$, the ensemble of signals is formed as:

$$S^{LPT} = \{s_1(t,\tau^*), s_2(t,\tau^*), \dots, s_P(t,\tau^*)\}. \quad (3)$$

In the generated ensemble of complex signals, each element is created by permuting the time segments according to the low-discrepancy lattice τ-sequence.

The block diagram of the LPT-τ permutation method is shown in Figure 1.

To validate the results of optimization performed using the integral criterion $K(\tau)$, a multiscale entropy analysis was conducted for the signal ensembles formed with the LPT-τ permutation method.

The purpose of the analysis is to quantitatively evaluate the degree of structural order, stability, and entropy-based complexity of the optimized signals compared to the initial ones. This makes it possible to assess how effectively the optimization criterion $K(\tau)$ preserves the internal organization of the ensemble and enhances its robustness under stochastic interference.

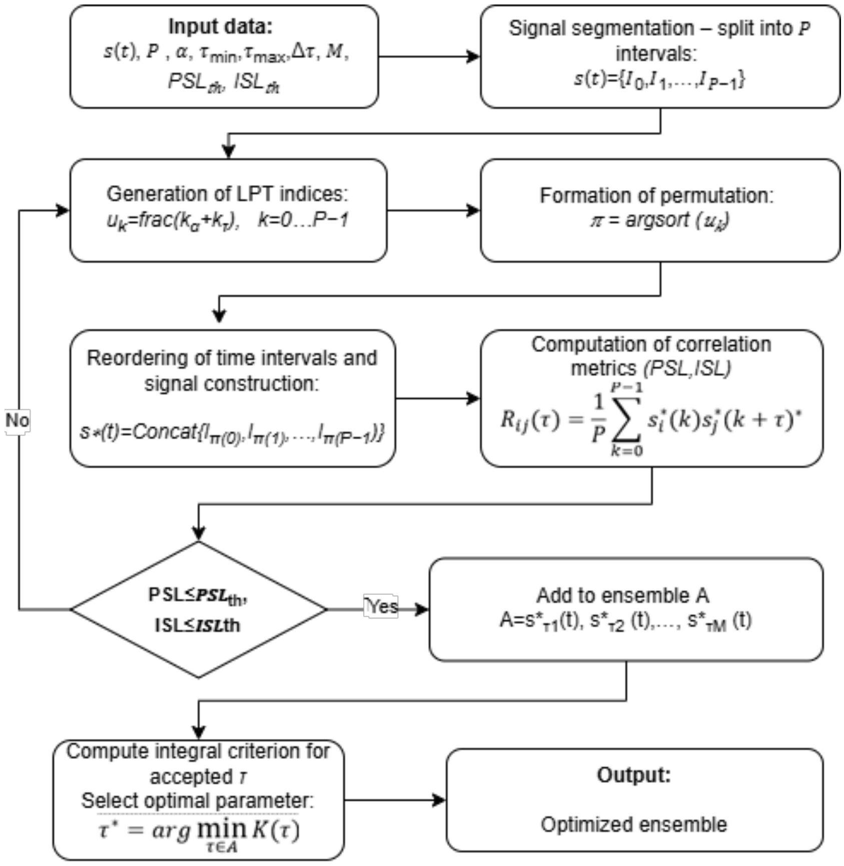

Fig. 1 Block diagram of the LPT-τ permutation method

Unlike the time permutation method based on Markov models, where the transition entropy $U(\pi_i)$ is a direct component of the optimization criterion $K(\pi_i)$ with the weighting coefficient β, in the LPT-TP method entropy is used to determine how well the obtained signal ensembles preserve structural order and predictability under stochastic interference.

To evaluate the dynamic properties of the signal ensembles, four main metrics of nonlinear time-series analysis were applied:

– Sample Entropy (SampEn) – measures the regularity and unpredictability of a time series;

– Permutation Entropy (PE) – quantifies the complexity of the signal based on the ordinal patterns of its values;

– Fuzzy Entropy (FuzzyEn) – assesses signal complexity using fuzzy membership functions to improve robustness;

– Dispersion Entropy (DispEn) – estimates the dispersion pattern distribution of amplitude values.

The analysis was carried out in a multiscale mode, where the scale factor varied from 1 to 10, corresponding to sequential coarse-graining of time series with different window lengths. To ensure the reproducibility of results, standard parameter settings were used: embedding dimension equal to two, time delay of one sample, and similarity tolerance of 0,2 times the standard deviation of the signal. These parameters correspond to the commonly accepted recommendations for computing SampEn and FuzzyEn, ensuring consistency with previous studies [1–4, 6, 13].

The experimental results are presented in Table 2 and Figure 2.

As can be seen from Table 2 and Figure 2, all entropy measures exhibit a stable dependence on both the signal-to-noise ratio (SNR) and the averaging scale.

For Sample Entropy, a monotonic increase is observed with growing scale, which indicates a decrease in local randomness as the temporal intervals are aggregated. Permutation Entropy, Fuzzy Entropy, and Dispersion Entropy show a U-shaped trend: entropy decreases at medium scales (3–6), reaching a minimum for optimized signals, and then gradually increases at larger scales due to the smoothing of fine structural details.

The lowest entropy values are characteristic of the optimized ensembles, indicating higher structural order and improved resistance to interference.

Table 2 – Entropy metrics of ensembles formed using the LPT-τ permutation method

Scale	SNR	Sample Entropy	Permutation Entropy	Fuzzy Entropy	Dispersion Entropy
1	–10 dB	0,38	0,95	0,90	0,70
	–5 dB	0,37	0,90	0,86	0,68
	0 dB	0,36	0,85	0,82	0,66
	5 dB	0,35	0,78	0,78	0,64
	10 dB	0,34	0,70	0,74	0,62
	Optimized	0,33	0,50	0,63	0,59
3	–10 dB	0,50	0,79	0,75	0,67
	0 dB	0,47	0,69	0,69	0,64
	Optimized	0,44	0,54	0,67	0,61
5	–10 dB	0,57	0,67	0,68	0,65
	0 dB	0,53	0,59	0,64	0,63
	Optimized	0,50	0,57	0,69	0,62
10	–10 dB	0,75	0,77	0,76	0,72
	0 dB	0,71	0,75	0,74	0,70
	Optimized	0,68	0,72	0,77	0,67

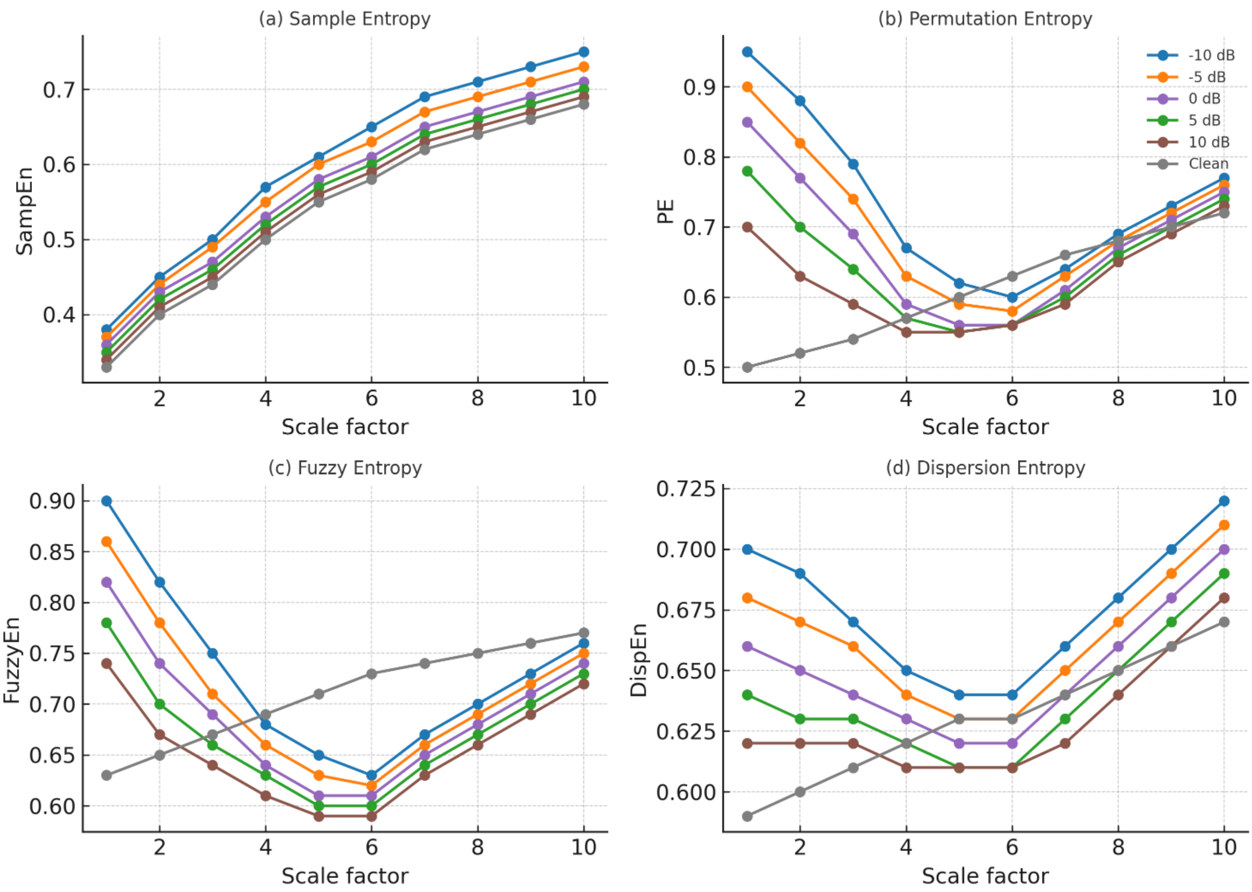

Fig. 2 Multiscale entropy analysis of signal ensembles formed using the LPT-τ permutation

For example, at scale 1, the value of permutation entropy decreases from 0,95 at SNR = –10 dB to 0,50 for the optimized signal, while FuzzyEn decreases from 0,90 to 0,63.

This trend is consistent across all selected metrics, confirming that the application of LPT-τ permutations ensures a controlled reduction of entropy-based complexity and the formation of ensembles with a higher degree of temporal structural order.

The next stage of the study involves evaluating the influence of the shift parameter τ on the entropy characteristics of the ensemble formed using the LPT-τ permutation method (Table 3, Figure 3). The objective of this stage is to determine the relationship between the optimization parameter τ^*, obtained from the criterion *K(τ)*, and the entropy indicators reflecting the ordering of signals.

Table 3 – Dependence of entropy metrics on the shift parameter τ

τ	Permutation Entropy	Fuzzy Entropy	Dispersion Entropy	Sample Entropy
0,2	0,569	0,576	0,509	0,489
0,38	0,596	0,608	0,506	0,544
0,5	0,739	0,726	0,664	0,644
0,618	0,687	0,68	0,589	0,619
0,8	0,79	0,771	0,711	0,691
0,9	0,797	0,778	0,717	0,697

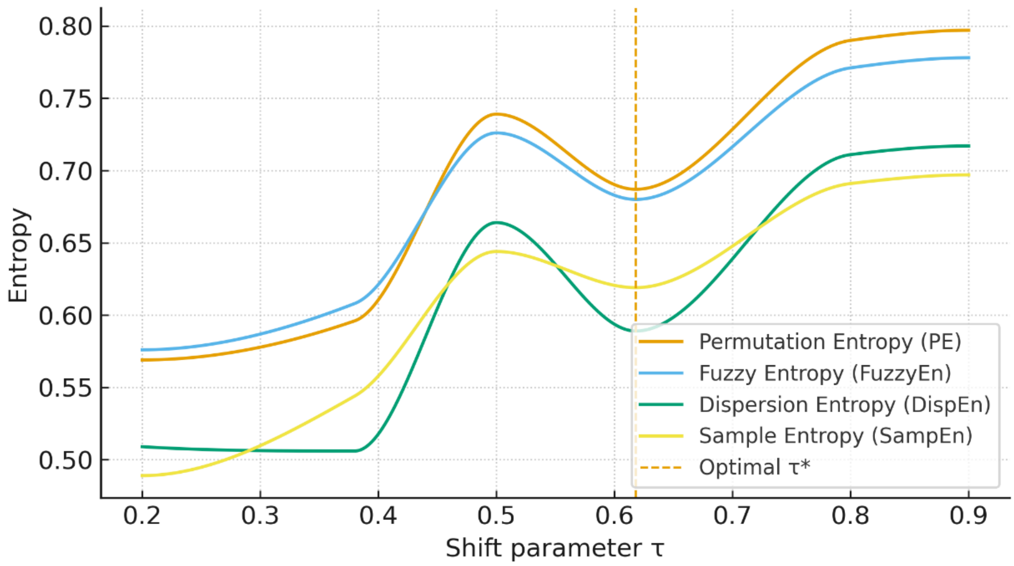

Fig. 3 Entropy metrics versus shift parameter τ

As shown by the experimental results (Table 3, Figure 3), all entropy indicators (PE, FuzzyEn, DispEn, and SampEn) vary consistently with the shift parameter *τ*. Within the range of intermediate values, a local minimum of entropy is observed, corresponding to the highest level of structural order in the ensemble. The dashed vertical line marks the optimal value τ^*, determined from the integral criterion *K(τ)*, which coincides with the region of minimums for all entropy indicators.

Quantitative evaluation shows that when *τ* decreases from 0,9 to its optimal value $\tau^* \approx 0{,}618$, the average entropy values decrease by approximately:

– ≈13,8 % for Permutation Entropy (PE),
– ≈12,6 % for Fuzzy Entropy (FuzzyEn),
– ≈17,9 % for Dispersion Entropy (DispEn),
– ≈11,2 % for Sample Entropy (SampEn).

Such a reduction indicates that the optimal parameter $\tau*$ ensures entropy consistency and confirms the effectiveness of the LPT-τ permutation method, which achieves an average increase in ensemble order of 12–18% compared with non-optimized ensembles.

However, this method has a static nature, since the optimization of τ^* is performed for a fixed ensemble state and does not account for the evolution of its structural and temporal characteristics in subsequent iterations.

To overcome this limitation, the study developed and conducted an experiment using a forecast-oriented time permutation method based on Markov models. Unlike the deterministic LPT-TP approach, the proposed method provides dynamic selection of permutations that takes into account the probabilistic transitions between the states of the signal ensemble, allowing adaptive reduction of the risk of transitions to high-correlation states.

The block diagram of the Markov-based method is presented in Figure 4.

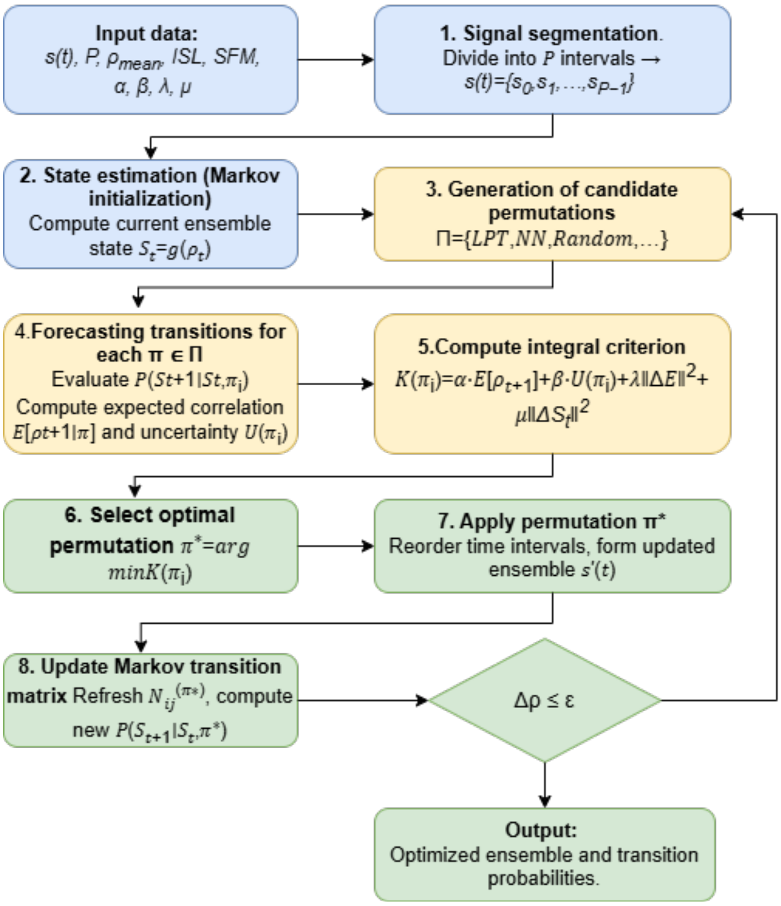

Fig. 4 Algorithm of the time-domain permutation method based on Markov models

To describe the dynamics of the ensemble, a Markov process with states $S(t)$ is used, where each state corresponds to the current level of ensemble order. The transition probabilities between states are determined according to the transition matrix defined by the analytical expression:

$$P(S_{t+1}|S_t,\ \pi_i) = \frac{N_{i,j}^{(\pi_i)} + u}{\sum_k \left(N_{i,k}^{(\pi_i)} + u\right)}, \qquad (4)$$

where $N_{i,j}^{(\pi_i)}$ is the number of transitions between states when applying the permutation π_i; u is the Laplace smoothing coefficient calculated to avoid zero transition probabilities between states.

The mathematical expectation of the predicted mutual correlation for each permutation is determined by the following expression:

$$E[\rho_{t+1}|\ \pi_i] = \sum\nolimits_{S_{t+1}} P(S_{t+1}|S_t,\ \pi_i)\cdot\rho(S_{t+1}), \qquad (5)$$

where $\rho(S_{t+1})$ is the average level of mutual correlation for the corresponding state.

The degree of forecast uncertainty is evaluated through the entropy of transition probabilities:

$$U(\ \pi_i) = -\sum\nolimits_{S_{t+1}} P(S_{t+1}|S_t,\ \pi_i)\log_2 P(S_{t+1}|S_t,\ \pi_i)\,. \qquad (6)$$

The integral optimization criterion is defined as follows:

$$K(\pi_i) = \alpha E[\rho_{t+1} | \pi_i] + \beta U(\pi_i) + \lambda \|\Delta E\|^2 + \mu \|\Delta S_t\|^2, \quad (7)$$

where $\alpha, \beta, \lambda, \mu$ are weighting coefficients; $\|\Delta E\|^2$ characterizes the deviation of the energy distribution of the signals; $\|\Delta S_t\|^2$ represents the measure of structural–temporal consistency of the ensemble after the permutation.

The minimum value of $K(\pi_i)$ corresponds to the optimal permutation π^*:

$$\pi^* = arg \min_{\pi_i \in \Pi} K(\pi_i). \quad (8)$$

As a result of this optimization, an updated ensemble of signals is formed:

$$S^{Markov}(t) = \pi^*(S(t)) = \{\pi^*(s_1(t)), \ldots, \pi^*(s_P(t))\}. \quad (9)$$

To validate the proposed method of optimizing ensembles of complex signals based on Markov models, an entropy analysis was performed with the calculation of the following indicators: the entropy measure of uncertainty $U(\pi_i)$, the mean mutual correlation coefficient ρ_{mean}, the integral optimality criterion $K(\pi_i)$ for the set of permutations *П*, as well as the entropy metrics used in the previous experiment with LPT-τ permutations: Sample Entropy, Permutation Entropy, Fuzzy Entropy, and Dispersion Entropy.

The purpose of the analysis is to provide a quantitative assessment of the stability, structural order, and entropy consistency of the ensemble of complex signals obtained as a result of optimization according to the forecast-oriented criterion based on Markov models.

During the simulation, three ensemble states were considered: Low, Medium, High, between which transitions occurred according to the Markov transition probability matrix $P(S_{t+1}|S_t, \pi_i)$.

To ensure reproducibility of the results, the following parameters were used: the number of iterations *N* = 20, the uncertainty weight coefficient β ∈ [0;1], the Laplace smoothing coefficient *u*=0,5, and the weighting coefficients α, β, λ, μ of the integral criterion, determined empirically.

The entropy analysis was performed for the optimized signal ensemble obtained after the convergence of the algorithm (at $\pi*$), in a multiscale mode to ensure correct comparison with the results obtained using the LPT–TP signal ensemble permutation method.

The simulation results are presented in Table 4 and Figure 5.

Table 4 – Entropy metrics of ensembles formed using the Markov-forecast method

Scale	SNR	Sample Entropy	Permutation Entropy	Fuzzy Entropy	Dispersion Entropy
1	−10 dB	0,39	0,97	0,91	0,71
	−5 dB	0,38	0,92	0,88	0,69
	0 dB	0,37	0,87	0,84	0,67
	5 dB	0,36	0,80	0,80	0,65
	10 dB	0,35	0,73	0,76	0,63
	Optimized	0.35	0,56	0,66	0,62
3	−10 dB	0,51	0,82	0,78	0,69
	0 dB	0,47	0,70	0,70	0,65
	Optimized	0,44	0,58	0,65	0,62
5	−10 dB	0,58	0,70	0,70	0,66
	0 dB	0,54	0,62	0,66	0,64
	Optimized	0,51	0,57	0,64	0,62
10	−10 dB	0,77	0,79	0,78	0,73
	0 dB	0,73	0,77	0,76	0,71
	Optimized	0,70	0,74	0,74	0,69

As shown in Table 4, all entropy indicators decrease as the signal-to-noise ratio (SNR) increases from –10 dB to +10 dB, indicating a gradual improvement in the structural order of the signal ensemble.

For the optimized ensemble obtained as a result of the convergence of the Markov algorithm, an additional reduction in entropy metrics is observed, averaging 8–15% compared with the baseline level at SNR = 0.

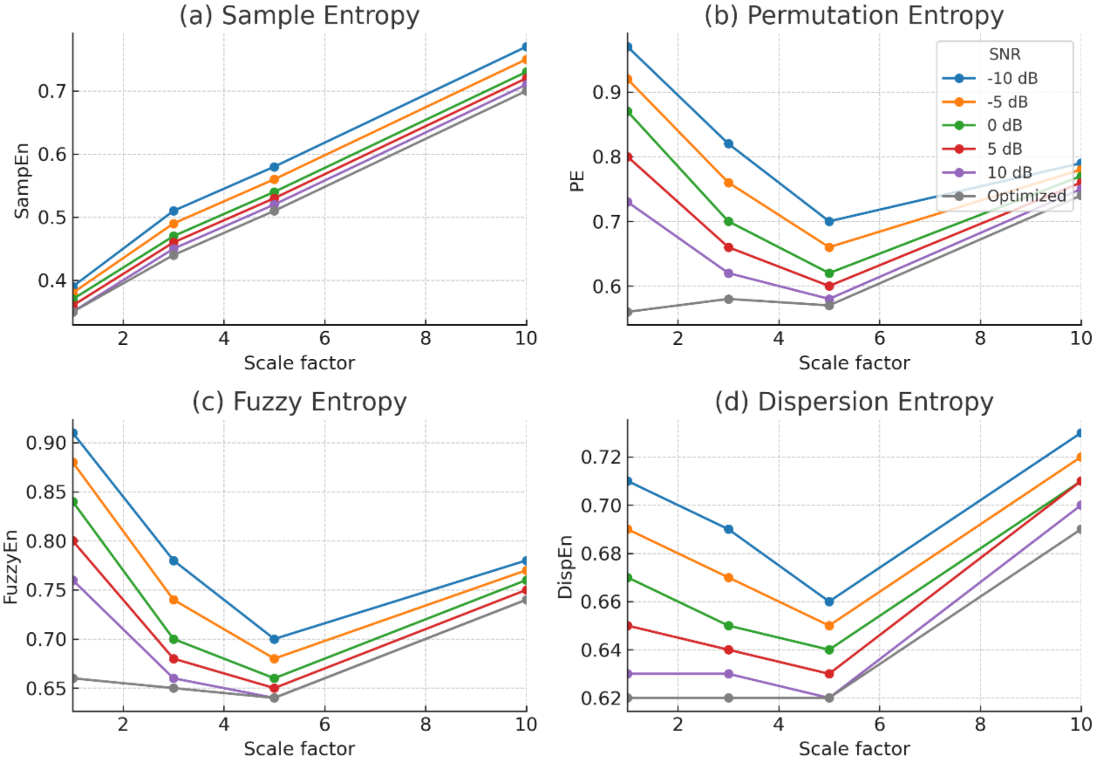

Fig. 5 Entropy analysis of signal ensembles formed using the Markov-forecast method

As shown in Figure 5, unlike the LPT-τ permutation method, where entropy reduction occurs more sharply (on average by 12–18%) due to deterministic ordering of time segments, the Markov-forecast method exhibits a smoother but more stable dynamic behavior. This can be explained by the fact that, in the Markov model, optimization is performed not through a fixed time shift but through probabilistic forecasting of state transitions within the ensemble. Such an approach provides adaptive smoothing of stochastic fluctuations and maintains a balance between structural order and energy stability of the signals.

For low SNR levels (–10 to –5 dB), all entropy indicators have increased values (PE ≈ 0,9–0,97, FuzzyEn ≈ 0,88–0,91), indicating a higher degree of uncertainty caused by interference. As the SNR increases to 10 dB, a steady decrease in PE and FuzzyEn values to about 0,73–0,76 is observed, which corresponds to an improvement in the structural order of the ensemble.

For the optimized state, entropy metrics reach their minimum values (PE = 0,56, FuzzyEn = 0,66 at scale = 1), confirming the convergence of the optimization process and a decrease in the entropy-based complexity of the system.

Thus, the Markov-forecast method provides a stable and gradual decrease in entropy metrics without abrupt fluctuations, indicating its dynamic stability and higher predictability of ensemble behavior compared to the deterministic LPT-τ permutation method.

For a more comprehensive analysis of the effectiveness of the Markov-forecast method, a study was conducted on the influence of the uncertainty coefficient β, which determines the weight of the entropy component $U(\pi_i)$ in the optimality criterion $K(\pi_i)$.

The calculation results are presented in Table 5 and Figure 6.

Table 5 – Dependence of entropy and correlation metrics on the uncertainty weight β

β	Transition entropy $U(\pi_i)$,	Mean correlation ρ_{mean}	Permutation entropy (PE)	Fuzzy entropy (FuzzyEn)	Integral criterion $K(\pi_i)$,
0,0	0,902	0,412	0,84	0,79	0,798
0,2	0,754	0,361	0,78	0,74	0,662
0,5	0,619	0,326	0,72	0,70	0,561
0,8	0,574	0,311	0,69	0,68	0,523

1,0	0,563	0,307	0,68	0,67	0,518

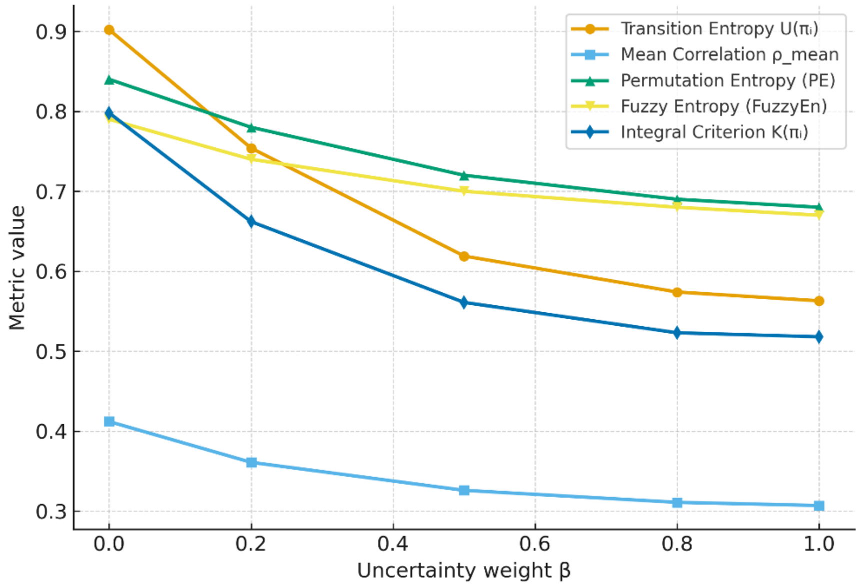

Fig. 6 Dependence of entropy metrics and integral criterion on the uncertainty weight β

As seen from Table 5 and Figure 6, an increase in the uncertainty coefficient leads to a gradual decrease in transition entropy, mean correlation, and the integral criterion, indicating stabilization of the Markov process and a reduction in stochastic uncertainty. At the same time, the values of local metrics (PE and FuzzyEn) also decrease, which reflects an improvement in the structural order of the ensemble.

Thus, the modeling results confirm that the optimal value of the uncertainty coefficient β lies within the range of 0,8–1,0, where the ensemble achieves its most balanced state with minimal entropy losses and maximum predictability of state transitions. This regime can be considered an optimal stability zone of the Markov process, ensuring structural consistency of the signals before generalizing the obtained results.

Conclusions and prospects for further research. The conducted research demonstrated that the method of forming ensembles of complex signals in the time domain based on LPT-τ permutations ensures a high degree of structural order and a reduction in entropy-based complexity. According to the results of multiscale analysis, the use of deterministic τ-sequences makes it possible to decrease entropy measures on average by 12–18% compared with non-optimized ensembles, confirming the improved predictability and stability of the signals. At the same time, the LPT-TP method has a static nature, since optimization is performed for a fixed ensemble state without considering its further temporal evolution. This limitation was overcome by developing a forecast-oriented approach based on Markov models, which provides dynamic optimization of permutations taking into account the transition probabilities between ensemble states. Experimental modeling results showed that as the uncertainty weight coefficient β increases from 0 to 1, a smooth decrease in transition entropy and average mutual correlation of approximately 35–40% is observed, indicating stabilization of the Markov process. The integral optimality criterion decreases by about 30%, while the permutation and fuzzy entropy values are reduced on average by 12–15%, confirming the achievement of higher structural consistency of the signals.

Thus, the Markov-forecast method provides improved predictability and dynamic stability of complex signal ensembles compared to the deterministic LPT-TP approach. Future research should focus on integrating Markov-based optimization with Bayesian predictive models and multilevel entropy regularization to improve ensemble performance under varying interference conditions in cognitive telecommunication networks.

Referens

1.Ahmed M. U., Mandic D. P. (2011) Multivariate multiscale entropy: A tool for complexity analysis of multichannel data, Physical Review E, vol. 84, no. 6, pp. 061918, 2011. DOI: https://doi.org/10.1103/PhysRevE.84.061918.

2.Azami H., Fernández A., and Escudero J. (2019) Multivariate multi-scale dispersion entropy of biomedical times series, Entropy, vol. 21, no. 9, pp. 913, 2019. DOI: https://doi.org/10.3390/e21090913.

3.Bandt C. and Pompe B. (2002) Permutation entropy: a natural complexity measure for time series, Physical Review Letters, vol. 88, no. 17, p. 174102, 2002. DOI: https://doi.org/10.1103/PhysRevLett.88.174102.

4.Chen W. et al. (2007) Characterization of surface EMG signal based on fuzzy entropy, Neural Systems and Rehabilitation Engineering, IEEE Transactions on, vol. 15, no. 2, pp. 266–272, 2007. DOI: 10.1109/TNSRE.2007.897025.
5.Chen, Z., Zhou, D., & Zio, E. (2019) Hidden Markov model with auto-correlated observations for degradation modeling of manufacturing systems. Reliability Engineering & System Safety, P.224–234, 2019. DOI: 10.1016/j.ress.2017.09.002.
6.Costa M., Goldberger A. L., and Peng C.-K. (2005) Multiscale entropy analysis of biological signals, Physical Review E, vol. 71, no. 2, p. 021906, 2005. DOI: https://doi.org/10.1103/PhysRevE.71.021906.
7.Dàvalos A., Jabloun M., Ravier P., and Buttelli O. (2019) Multi-scale permutation entropy: Statistical characterization on au-toregressive and moving average processes, in 2019 27th Eu-ropean Signal Processing Conference, pp. 1–5. https://www.eurasip.org/Proceedings/Eusipco/eusipco2019/Proceedings/papers/1570533150.pdf.
8.Fabila-Carrasco J.S., Tan C., and Escudero J. (2022) Permutation entropy for graph signals, IEEE Transactions on Signal and Information Processing over Networks, vol. 8, pp. 288–300, 2022. DOI: https://doi.org/10.1109/TSIPN.2022.3167333.
9.Fan C.L., Jin N.D., Chen X.T., Gao Z.K. (2013) Multi-scale permutation entropy: A complexity measure for discriminat-ing two-phase flow dynamics, Chinese Physics Letters, vol. 30, no. 9, pp. 090501, 2013. DOI: 10.1088/0256-307X/30/9/090501.
10. Indyk S. V., Lysechko V. P., Kulagin D. O., Zhuchenko O. S., Kovtun I. V. (2022) The study of the cross-correlation properties of complex signals ensembles obtained by filtered frequency elements permutations. Radio Electronics, Computer Science, Control. National University «Zaporizhzhia Polytechnic». Issue 2 (61), pp. 15–23, 2022. DOI: 10.15588/1607-3274-2022-2-2.
11. Indyk S., Lysechko V. The formation method of complex signals ensembles with increased volume based on the use of frequency bands. Control, navigation and communication system. Issue 4 (62), pp. 119-121, 2020. DOI: 10.26906/SUNZ.2020.4.119.
12. Morabito F.C. et al. (2012) Multivariate multi-scale permutation entropy for complexity analysis of Alzheimer's disease EEG, Entropy, vol. 14, no. 7, pp. 1186–1202, 2012. DOI: https://doi.org/10.3390/e14071186.
13. Rostaghi M. and Azami H. (2016) Dispersion entropy: A measure for time-series analysis, IEEE Signal Processing Letters, vol. 23, no. 5, pp. 610-614, 2016. DOI: https://doi.org/10.1109/LSP.2016.2542881.
14. Yin Y. and P. Shang, (2017) Multivariate weighted multiscale permutation entropy for complex time series, Nonlinear Dynamics, vol. 88, no. 3, pp. 1707–1722, 2017. https://2024.sci-hub.box/7712/1789b1b5d42a491b4119805aef3eedce/wang2019.pdf.
15. Kuznichenko, V. M. (2010). Entropy of states of Markov chains in a linear model of international trade. Bulletin of the National Technical University «KhPI». Series: Technical Progress and Production Efficiency, 58, pp. 14–20, 2010. https://repository.kpi.kharkov.ua/handle/KhPI-Press/28731