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Oleksii Shevchenko, Post-Graduate Student
Ukrainian State University of Railway
Transport. https://
orcid.e-mail: braleksey_2003@ukr.net;

Volodymyr Lysechko, Dr Sc. Professor
Scientific Center of the Air Force Ivan Kozhedub Kharkiv National University of Air Forces
https://orcid.org/0000-0002-1520-9515
e-mail: lysechkov@ukr.net

METHOD OF TIME PERMUTATIONS BASED ON MARKOV MODELS

Introduction

In telecommunication networks with multiple access, one of the primary tasks is to maintain the stability of signals within a shared frequency environment. As the number of users increases and the structure of transmitted signals becomes more complex, mutual interference intensifies, which leads to higher levels of inter-channel and inter-symbol distortions. As a result, the correlation and spectral characteristics of the signal ensemble degrade, the peak values of correlation functions increase, the uniformity of energy distribution is disturbed, and the temporal coherence of the ensemble structure decreases [1, 2].

There is a functional relationship between the noise immunity of the ensemble, its size, and its cross-correlation properties. Lower mutual correlation coefficients allow a larger ensemble size without losing stability, while increasing the ensemble size raises the risk of higher correlation components and, consequently, inter-symbol interference. Therefore, the relevant task is to form signal ensembles in which a controlled balance between noise immunity, ensemble size, and cross-correlation characteristics is achieved.

One effective approach to achieving this balance is to control the temporal organization of signals within the ensemble by permuting time intervals (segments), which directly influences the correlation and structural properties of the ensemble in the time domain.

To describe the evolution of the ensemble and to predict changes in its characteristics under various time-segment permutations, it is appropriate to use models that can represent the sequence of ensemble states. Markov modeling provides such capabilities by allowing the tracking of ensemble state dynamics and performing predictive optimization of permutations aimed at reducing mutual correlation while maintaining the structural stability of the ensemble [3, 4, 5].

Analysis of recent research and publications

An analysis of scientific studies [1–15] has shown that the novelty of the proposed approach lies in the integration of probabilistic Markov modeling with deterministic optimization techniques, which were previously applied separately.

Studies [1, 2] focused on the formation and analysis of ensembles of complex signals through time-interval permutation and established the influence of correlation properties on ensemble scalability. However, these works did not include probabilistic modeling of the ensemble evolution or predictive control of correlation growth.

The approaches proposed in [3–5] introduced ensemble hidden Markov models for dynamic signal characterization, biosignal interpretation, and target detection. These studies demonstrated the potential of Markov modeling for describing probabilistic state transitions but did not address its application to time-domain permutation or ensemble correlation optimization.

Research [6–9] expanded the field toward nonlinear signal reconstruction, gradient and Lagrange optimization, and the use of Volterra series for stability and orthogonality control. Yet these methods were limited to deterministic reconstruction and lacked adaptive probabilistic feedback mechanisms.

The works [10–12] developed multilevel and adaptive techniques for time-frequency segmentation and ensemble formation, showing improvements in signal structure and scalability. Nevertheless, they mainly relied on direct optimization and did not integrate predictive modeling of ensemble state transitions.

The study in [13] proposed a correlation-based pruning method for large-scale MIMO communication, confirming the practical importance of minimizing cross-correlation under interference, but without addressing time-domain ensemble adaptation.

Finally, papers [14, 15] highlighted the effectiveness of Markov and hidden Markov models in modeling stochastic and degradation processes, supporting the feasibility of their use for predictive modeling of signal ensembles.

In summary, the reviewed works laid the foundation for ensemble formation, optimization, and correlation control; however, none combined time-interval permutation with forecast-oriented Markov modeling. This gap motivates the present study, which integrates probabilistic state prediction and integral optimization criteria to achieve stable and scalable ensemble formation under high interference conditions.

Problem Statement

This study addresses the problem of optimizing ensembles of complex signals in the time domain under conditions of stochastic uncertainty and a high level of interference, where classical deterministic permutation procedures fail to provide stable reduction of mutual correlation and preservation of energy–spectral balance [6–10].

Under such conditions, it becomes relevant to apply a method capable of describing the evolution of ensemble states and predicting state transitions during time-interval permutations, which enables prior estimation of the risk of increasing correlation peaks and loss of temporal coherence [11–13].

To solve this problem, it is necessary to employ a forecast-oriented approach based on Markov models with transition probabilities that depend on the selected permutation, combined with an integral selection criterion that incorporates the expected level of mutual correlation, the degree of forecast uncertainty, energy uniformity, and structural–temporal consistency [14–15].

The purpose of the article

The aim of the study is to develop a forecast-oriented method based on Markov models for optimizing ensembles of complex signals in the time domain under conditions of a high level of interference and stochastic uncertainty, ensuring controlled reduction of mutual correlation while maintaining energy–spectral balance and structural–temporal coherence.

Summary of the main material

The distinctive feature of the proposed method of time-interval permutations for ensembles of complex signals is the use of Markov models [3, 4, 5] to predict the evolution of the ensemble state in the time domain.

The Markov approach was chosen due to its ability to describe probabilistic transitions between successive states of a complex signal ensemble, where the current state depends only on the previous state of the system [4].

This property, known as the limited-memory condition of the process, enables the construction of a stationary stochastic model of the ensemble, in which the prediction of the next state is performed based on transition probabilities without the need to account for the complete history of previous realizations.

Such characteristics make the Markov approach optimal for modeling permutation processes of complex signal ensembles in the time domain, where it is important to reproduce not only the current structure of the ensemble but also its expected dynamics in subsequent iterations.

Figure 1 shows the logic of constructing the Markov model adapted for forecast-oriented time-interval permutations of the signal ensemble.

As shown in Figure 1, Step 1 represents the basic Markov chain that describes changes in the states of the complex signal ensemble without considering the permutation process.

At Step 2, a forecast-oriented temporal unfolding is implemented, in which the transitions between states are defined by probabilities $P((S_{t+1}|S_t, \pi))$, that depend on the selected permutation π.

This combination makes it possible to predict changes in the correlation characteristics of the ensemble and to select the permutation that minimizes the risk of transitions to states with increased mutual correlation.

Let us consider in more detail the stages of implementing the proposed forecast-oriented method of time-interval permutations for signal ensembles, which is built on a Markov model. For practical use, the method is presented as an algorithm that consists of successive procedures for prediction, evaluation, and selection of the optimal permutation π^* (Fig.2).

In Fig. 2, the main stages of the proposed method are highlighted in different colors:

– blue indicates the stages of initialization and data input;

– yellow corresponds to the processes of prediction and calculation of the optimality criterion $K(\pi)$;

– green represents the stages of selecting the optimal permutation π^* and forming the optimized signal ensemble;

– purple shows the sequence of observed states X_0, X_1, X_2, X_3, which reflect the evolution of the ensemble characteristics over time during the forecast-oriented permutation process.

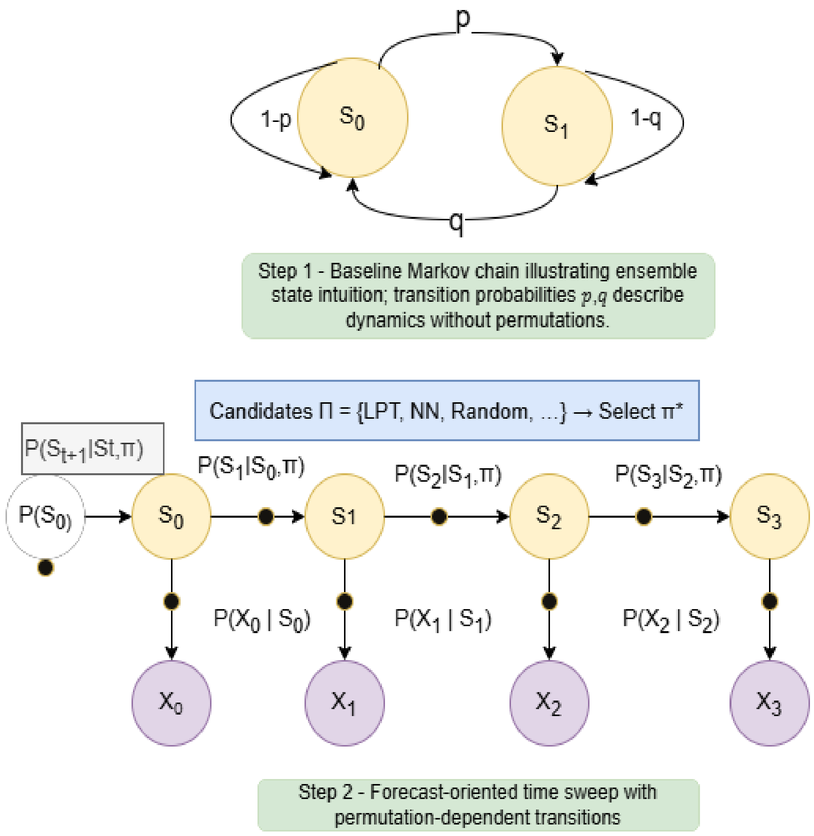

Fig.1. Logic of constructing the forecast-oriented Markov permutation model

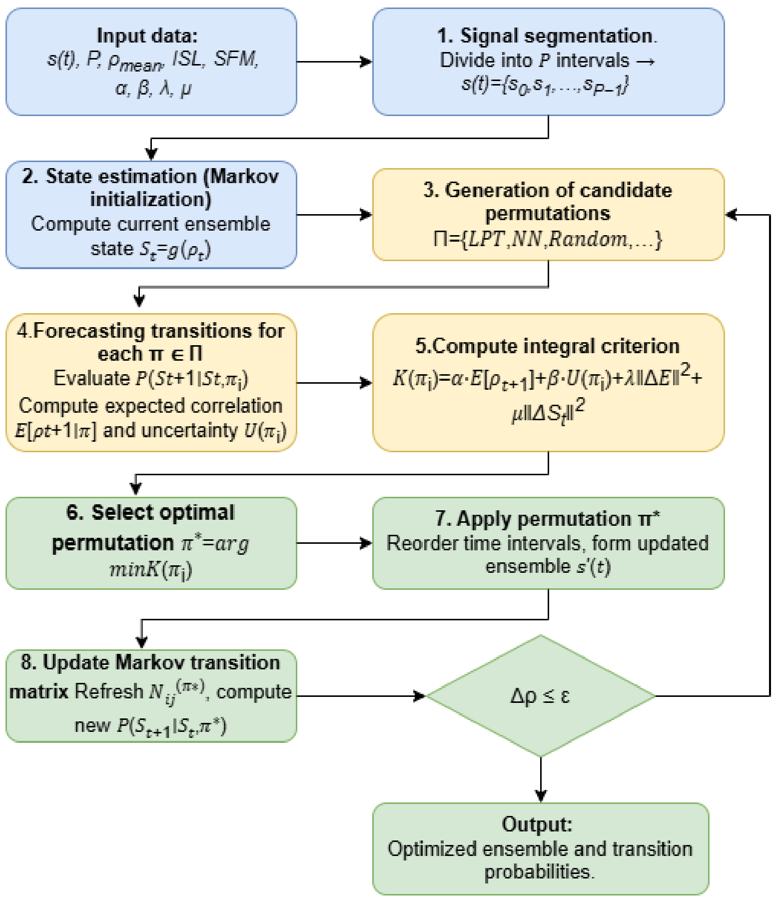

Fig. 2. Algorithmic structure of the forecast-oriented Markov permutation method

Step 1. Signal segmentation and formation of the permutation set

At the initial stage, the ensemble of complex signals $S(t)$ is divided into time segments, which allows further permutation of these segments within the given ensemble.

Each signal $s_i(t)$ is represented as a combination of K non-overlapping time intervals, as shown in the analytical expression (1):

$$s_i(t) = \bigcup_{k=1}^{K} s_{ik}(t_k),\ i=1,\dots,P \tag{1}$$

where $s_{ik}(t_k)$ denotes the k – th time segment of the i-th signal, and K is the number of segments into which the signal is divided.

The set of all signals forms the ensemble $S(t)$, which is defined by expression (2):

$$S(t) = \{s_1(t), s_2(t), \dots, s_P(t)\}. \tag{2}$$

Based on the formed ensemble, a set of possible time-segment permutations Π_K is generated.

Each permutation π is an operator that defines a new temporal configuration of the ensemble according to expression (3):

$$\pi\big(S(t)\big) = \{\pi(s_1(t)), \dots, \pi(s_P(t))\}, \pi \in \Pi_K \tag{3}$$

Thus, at the first stage, the solution space is formed, represented by the set of permutations Π_K, within which the search for the optimal permutation is carried out at subsequent stages.

Depending on the specific task, the permutations can be generated according to different principles [1, 2, 6–9, 13].

1. Deterministic methods include approaches in which the order of segments is defined by an analytical rule or an optimization principle that ensures uniformity of the ensemble's temporal structure. These may involve permutations based on evenly distributed or centered sequences.

2. Stochastic methods involve selecting permutations randomly or according to statistical criteria, which increases the diversity of ensemble realizations and helps avoid local extrema during optimization. Examples include random, probabilistically weighted, or evolutionarily generated permutations.

The use of both groups of methods provides a balance between predictability and variability of ensemble structures, which serves as a foundation for further forecast-oriented permutation selection.

Step 2. Evaluation of the current state of the signal ensemble (Markov initialization)

At the second stage, a quantitative evaluation of the correlation characteristics of the complex signal ensemble is performed at the current time moment t.

For each signal $s_i(t)$, the average and maximum values of mutual correlation (ρ_{mean}, ρ_{max}) between time segments are calculated, along with additional parameters such as the Integrated Sidelobe Level (ISL) and the Spectral Flatness Measure (SFM).

Based on these indicators, the current state of the ensemble $S(t)$ is determined, reflecting the degree of its structural order. To simplify the analysis, it is assumed that the set of possible states is finite and can be formalized analytically as follows (4):

$$S(t) \in \{Low, Mid, High\}, M = 3. \tag{4}$$

Such discretization makes it possible to represent the behavior of the ensemble as a Markov chain, where transitions between states occur with certain probabilities $P(S_{t+1}|S_t)$.

The initialization of this chain is based on the current values of ρ_{mean} and ISL, which provides an analytical basis for further prediction of state transitions. For visualization, see Fig. 1, which shows the dynamics of transitions between different ensemble states according to the Markov model.

However, at this stage, no permutations are performed yet. Instead, an initial conceptual model of the ensemble's evolution is formed, which is necessary for forecast-oriented control in the subsequent stages of the proposed method.

Step 3. Formation of the set of candidate permutations in the time domain and forecast-oriented evaluation of transitions.

At the third stage, a set of possible permutations of time segments $\Pi = \{\pi_1, \pi_2, \dots, \pi_N\}$ is generated, where each permutation defines an alternative temporal configuration of the complex signal ensemble.

Candidate permutations in the time domain can be generated either deterministically (for example, based on uniformly distributed sequences using the LPT method) or stochastically (using random permutation or the nearest neighbor method, NN).

For each permutation π_i, the future state of the ensemble is predicted using the Markov model as the transition probability $P(S_{t+1}|S_t,\ \pi_i)$.

In the proposed method, the prediction is performed taking into account the uncertainty coefficient β, which determines the weighting penalty for prediction instability.

This parameter serves as a regulator that balances the intensity of reducing the mutual correlation level ρ_{mean} and the stability of transitions between the ensemble states S_t.

At low values of β, there is an active reduction of ρ_{mean}, which leads to increased variability of states and fluctuations in the temporal structure of the ensemble. At higher values of β, the system operates in a more balanced mode, characterized by smoother transition processes and, as a result, improved temporal consistency of the signals.

To evaluate the influence of the parameter β on the stability of ensemble states and the level of mutual correlation between signals, a simulation was carried out at a signal-to-noise ratio (SNR) of 10 dB. The results are presented in Table 1.

Table 1

Influence of β on correlation and state-switching dynamics

β	ρ_{mean}	Number of state transitions
0,00	0,276	38
0,05	0,281	31
0,15	0,284	22
0,30	0,296	15

As shown in Table 1, an increase in the parameter β is accompanied by a monotonic decrease in the frequency of state transitions within the ensemble, while the average mutual correlation ρ_{mean} increases only slightly.

Figure 3 shows the nature of this relationship. As can be seen from the graph, at β ≈ 0,15, the ensemble reaches an optimal operating mode in which the minimum level of mutual correlation is achieved while maintaining temporal stability and structural order of the signal ensemble. This fully corresponds to the theoretical model of Markov-based transition control.

Step 4. Prediction of transitions and calculation of the integral optimality criterion

At the fourth stage, the state of the ensemble is predicted after applying each candidate permutation $\pi_i \in \Pi$.

The prediction is based on the Markov model, which takes into account the current state of the ensemble S_t and the probability of transition to the next state S_{t+1}, according to the analytical expression (5).

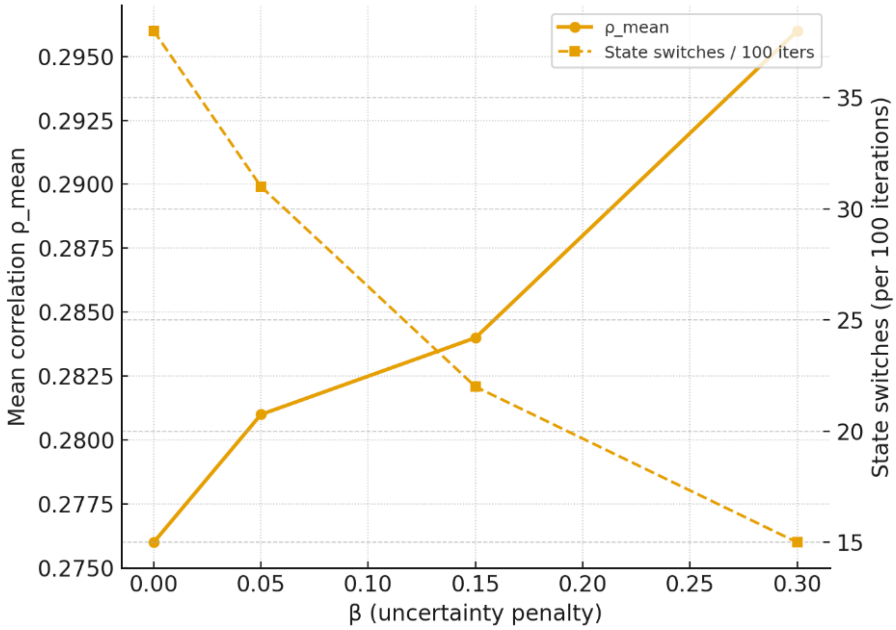

Fig. 3. Influence of the parameter β on correlation and the frequency of state transitions

$$P(S_{t+1}|S_t, \pi_i) = \frac{N^{(\pi_i)}_{S_t,S_{t+1}} + u}{\sum_{S_{t+1}}\left(N^{(\pi_i)}_{S_t,S_{t+1}} + u\right)}, \quad (5)$$

where $N^{(\pi_i)}_{S_t,S_{t+1}}$ is the number of recorded transitions between ensemble states for the permutation π_i, and u is the Laplace smoothing coefficient used to avoid zero probabilities.

Based on these estimates, the mathematical expectation of the predicted level of mutual correlation is calculated according to formula (6):

$$E[\rho_{t+1}|\,\pi_i] = \sum_{S_{t+1}} P(S_{t+1}|S_t, \pi_i)\cdot\rho(S_{t+1}), \quad (6)$$

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

Additionally, the degree of forecast uncertainty is taken into account, which is evaluated according to formula (7) through the entropy of the transition probability distribution:

$$U(\pi_i) = -\sum_{S_{t+1}} P(S_{t+1}|S_t, \pi_i)\log_2 P(S_{t+1}|S_t, \pi_i). \quad (7)$$

For a generalized evaluation of the quality of each permutation π_i, the integral optimality criterion is calculated according to formula (8):

$$K(\pi_i) = \alpha E[\rho_{t+1}|\,\pi_i] + \beta U(\pi_i) + \lambda\|\Delta E\|^2 + \mu\|\Delta S_t\|^2, \quad (8)$$

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^*, that is, $K(\pi^*)$:

$$\pi^* = arg \min_{\pi_i \in \Pi} K(\pi_i), \quad (9)$$

According to condition (9), the selected permutation ensures forecast-oriented minimization of mutual correlation while simultaneously controlling the energy and structural–temporal characteristics of the ensemble.

Fig. 4 shows the dependencies of the integral criterion $K(\pi^*)$ and the average correlation ρ_{mean} on the iteration number. After 10–12 iterations, the indicators become stable, which confirms the convergence of the method and the stability of the optimization process.

Stage 5. Updating the transition matrix and forming the renewed signal ensemble.

After selecting the optimal permutation $\pi*$ according to condition (9), the Markov model of the ensemble is updated to account for the new states obtained as a result of applying this permutation.

The updating procedure consists in recalculating the transition probabilities between states and adapting the Markov transition matrix, which describes the dynamics of the ensemble in the new temporal configuration.

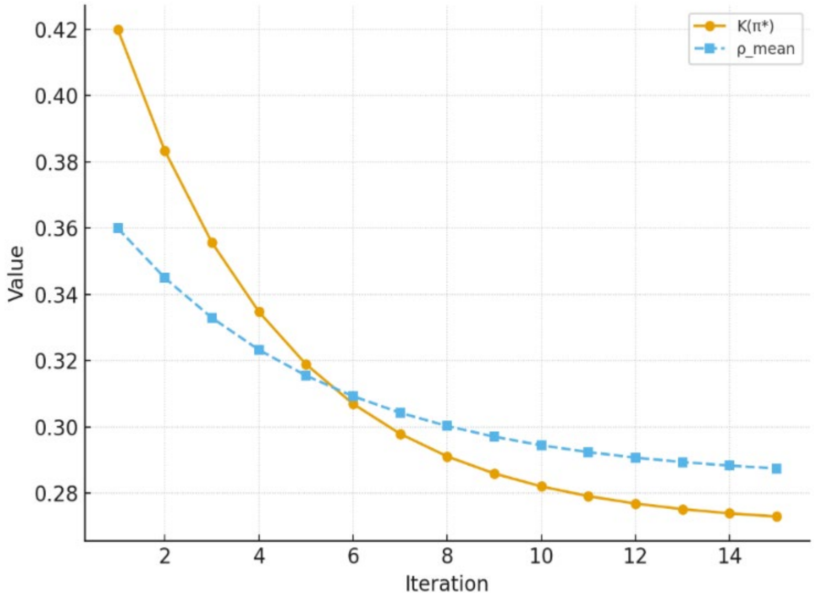

Fig. 4. Convergence of the forecast-oriented permutation selection algorithm

The Markov transition matrix is updated according to equation (10):

$$P^{new}(S_{t+1}|S_t, \pi^*) = \frac{N^{new(\pi_i)}_{S_t,S_{t+1}} + u}{\sum_{S_{t+1}} \left(N^{new(\pi_i)}_{S_t,S_{t+1}} + u\right)}, \quad (10)$$

where $N^{new(\pi_i)}_{S_t,S_{t+1}}$ denotes the number of state transitions in the ensemble after applying the optimal permutation.

The updated Markov transition matrix is then used to form a new signal ensemble *S′(t)*, in which the time segments are reordered according to the optimal permutation, as expressed in equation (11):

$$S'(t) = \pi^*\big(S(t)\big) = \{\pi^*(s_1(t)), \dots, \pi^*(s_P(t))\}. \quad (11)$$

At this stage, the condition of ensemble balance is also verified: $|\Delta\rho| \le \varepsilon$, meaning that the change in the average mutual correlation coefficient between consecutive iterations is monitored with respect to the threshold value ε, which determines the termination of the optimization process.

If the condition is satisfied, the signal ensemble is considered stabilized and fixed in the current state $S'(t)$, which corresponds to the minimal mutual correlation between signals.

If the condition is not met, the implementation algorithm of the proposed method returns to Stages 3–4 for repeated refinement of the permutation and transition prediction.

Thus, Stage 5 completes the full cycle of forecast-oriented ensemble optimization.

At this stage, the algorithm finalizes the iterative adaptation process and produces the resulting ensemble of complex signals. The obtained ensemble is characterized by a consistent temporal organization, which ensures coherence between its segments, and by a minimized level of mutual correlation, which reduces the interference between signals.

Additionally, the Markov transition model is adaptively updated to reflect the actual dynamic behavior of the ensemble after optimization. This allows the model to retain predictive capability for further iterations or for application in real-time signal processing, ensuring the stability, adaptability and reproducibility of the proposed method.

For the experimental verification of the proposed method, an ensemble of 128 signals typical for modern broadband telecommunication systems was used.

The sampling rate was set to 10 MHz to ensure accurate representation of the time–frequency structure of the signals. Each signal was divided into $P = 16$ time segments, for which the average and maximum mutual correlation coefficients (ρ_{mean}, ρ_{max}), integrated sidelobe level (ISL), and spectral flatness measure (SFM) were calculated. These parameters were used to evaluate the current ensemble state and to forecast its subsequent dynamics using the Markov model.

The number of states in the Markov model was set to $M = 3$, corresponding to low, medium, and high correlation levels (Low, Mid, High). The transition probabilities $P(S_{t+1}|S_t, \pi)$ were estimated over ten iterations using the Laplace smoothing coefficient $u = 0{,}5$.

Experiments were conducted under several interference scenarios with signal-to-noise ratios SNR = = 0, 5, 10, and 20 dB. The stopping criterion was defined as $|\rho(t+1) - \rho(t)| \leq 0{,}01$.

To compare the efficiency of the proposed method, three baseline permutation techniques were implemented: the random permutation method (Random), the nearest-neighbor method (NN), and the low-discrepancy time sequence method (LPT). The obtained results were compared with those produced by the proposed forecast-oriented Markov-based method (Markov-forecast). Each experiment was repeated 30 times, and the results were averaged to derive stable trends. The averaged performance indicators for different SNR values are summarized in Table 2 and illustrated in Fig. 5.

Table 2

Comparison of the efficiency of methods at different SNR

Method	*SNR*	0	5	10	20
Random	ρ_{mean}	0,496	0,451	0,422	0,409
	ISL (dB)	–5,1	–5,8	–6,1	–6,3
	SFM	0,67	0,69	0,71	0,72
LPT	ρ_{mean}	0,401	0,372	0,348	0,336
	ISL (dB)	–6,3	–6,9	–7,4	–7,7
	SFM	0,72	0,73	0,75	0,76
NN	ρ_{mean}	0,374	0,348	0,326	0,315
	ISL (dB)	–6,8	–7,4	–7,9	–8,2
	SFM	0,74	0,76	0,77	0,78
Markov-forecast	ρ_{mean}	0,341	0,309	0,284	0,272
	ISL (dB)	–7,7	–8,4	–9,0	–9,4
	SFM	0,77	0,79	0,81	0,83

As seen from the obtained results, the proposed Markov-forecast method demonstrates the best ensemble performance across all SNR levels.

Even at a low SNR of 0 dB, the average correlation coefficient ρ_{mean} 14 % lower than that of the NN method and about 31 % lower than that of the random permutation method.

At SNR = 20 dB, the positive trend remains – ρ_{mean} decreases by nearly 33 %, while the integrated sidelobe level (ISL) improves by approximately 3 dB.

The spectral flatness measure (SFM) increases from 0,72 to 0,83, indicating enhanced spectral uniformity and structural balance within the signal ensemble. These results clearly demonstrate the efficiency of the proposed method, which consistently preserves the ensemble's structure and spectral coherence under varying interference conditions.

The obtained results confirm that the proposed forecast-oriented permutation selection method based on the Markov model provides high noise immunity and structural stability of the signal ensemble.

This means that during the optimization process, the temporal organization of signals, the uniformity of energy distribution, and the consistency of correlation–spectral characteristics are preserved even under high interference conditions. As a result, the ensemble maintains its internal order and the ability to sustain the required volume without loss of stability or parameter balance.

The proposed time-interval permutation method with forecast-oriented selection based on the Markov model ensures controlled reduction of mutual correlation while simultaneously maintaining energy balance and structural–temporal alignment of the ensemble.

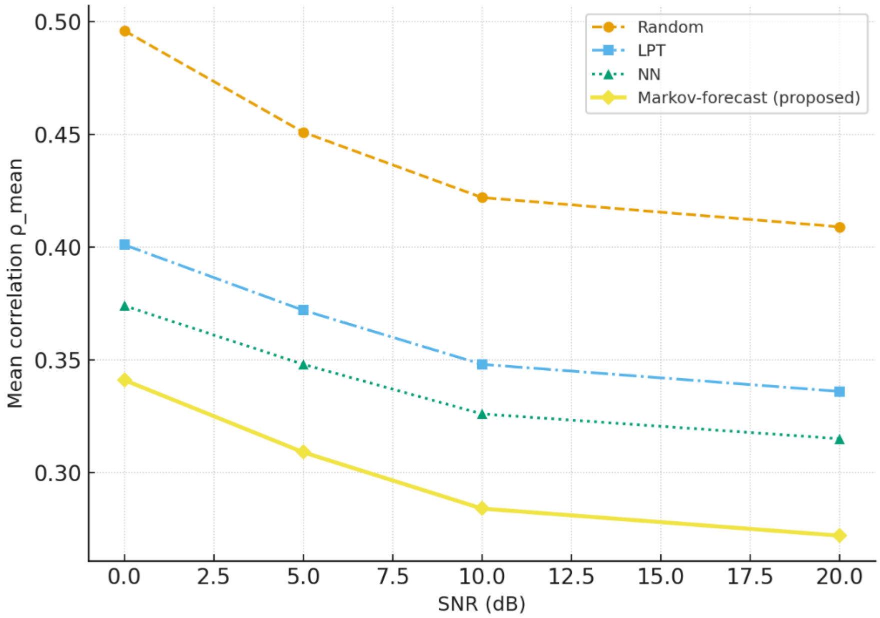

Fig.5. Dependence of the mean correlation coefficient on SNR for different permutation methods

Conclusions

The time-interval permutation method with forecast-oriented selection based on Markov models proposed in this study is a comprehensive approach. Unlike existing methods, it simultaneously integrates parametric analysis, signal segmentation, prediction of ensemble state transitions, and an integral evaluation of permutation optimality.

The use of the Markov model makes it possible to predict the evolution of the ensemble without the need to store the complete history of its previous states, which reduces computational complexity and improves the controllability of the optimization process.

Experimental results have shown that increasing the number of time segments reduces the average mutual correlation coefficient by approximately 33 % compared to the nearest-neighbor method (NN) and by about 31 % compared to the random permutation method. The integrated sidelobe level (ISL) improved by approximately 3 dB, and the spectral flatness measure (SFM) increased from 0,72 to 0,83, indicating a higher degree of structural order within the ensemble and greater temporal consistency of the signal intervals.

Introducing the uncertainty coefficient β into the proposed method allowed balancing the rate of decorrelation and ensemble stability. Experimental calculations showed that the optimal value of $\beta \approx 0{,}15$ reduces the frequency of state transitions by about 60 % while having a minimal effect on the level of mutual correlation between signals.

The algorithm converges within 10–12 iterations, confirming the efficiency of forecast-based control using Markov models and the stability of the integral criterion. Therefore, the proposed method ensures stable formation of complex signal ensembles in the time domain, increases noise immunity, and maintains the stability of temporal characteristics, making it suitable for application in cognitive telecommunication networks.

REFERENCES

[1] Indyk S., Lysechko V. The study of ensemble properties of complex signals obtained by time interval permutation. *Advanced Information Systems*. 2020. Vol. 4, № 3.-P. 85-88. https://doi.org/10.20998/2522-9052.2020.3.11.

[2] Indyk S., Lysechko V. Method of permutation of intervals, taking into accountant correlation properties of segments. *Control, navigation and communication system*. 2020. Issue 3 (61). P. 128–130. DOI:10.26906/SUNZ.2020.

[3] Rezek I., Roberts S. J., & Sykacek P. (2003). Ensemble coupled hidden Markov models for joint characterisation of dynamic signals. In Proceedings of the 3rd International Conference on Independent Component Analysis and Blind Signal Separation (ICA 2003). PP. 615–620. Springer. https://proceedings.mlr.press/r4/rezek03a/rezek03a.pdf.

[4] Rezek I., & Roberts S. (2001). Ensemble hidden Markov models with extended observation densities for biosignal analysis. Department of Engineering Science, University of Oxford. https://www.robots.ox.ac.uk/~irezek/Outgoing/Papers/varhmm. pdf.

[5] Hamdi A., & Frigui H. (2015). Ensemble hidden Markov models with application to landmine detection. *EURASIP Journal on Advances in Signal Processing*, 2015(1), 76. https://asp-eurasipjournals.springeropen.com/articles/10.1186/s13634-015-0260-8.

[6] Komar O., Lysechko V., Tarshin V., Mysyura O., Bezverkhy S. Complex signals parameters optimization on the base of linear approximations using the gradient method and Newton's method. *Information and control systems in railway transport: scientific and technical journal*. Kharkiv: UkrDUZT, 2024. No. 3(29). P. 74–83. DOI: https://doi.org/10.18664/ikszt.v29i3.313786.

[7] Perets K., Komar O., (2025) Optimization method using Lagrange multipliers to ensure conditions of orthogonality and stability of signal reconstruction. – Національний авіаційний університет. *Наукоємні технології*, 2025. Том. 65, № 1, С. 69–76, https://doi.org/10.18372/2310-5461.65.19927.

[8] Lysechko V. P., Komar O. M., Veklych O. K., Bershov V. S. Optimization of the parameters of synthesized signals using linear approximations by the nelder-mead method. National University «Zaporizhzhia Polytechnic». *Radio Electronics, Computer Science, Control*, 2024, 3 (70), P. 35–43 DOI: https://doi.org/10.15588/1607-3274-2024-3-4 (Web Of Science – 2024).

[9] Perets K., & Zhuchenko O. Method of localized signal reconstruction in dynamic environments based on modified Volterra series. *Computer-integrated technologies: education, science, production*. Lutsk National Technical University. Lutsk. 2025. (№ 59). P.P. 313–321. https://doi.org/10.36910/6775-2524-0560-2025-59-39.

[10] Veklych O. Drobyk O. Justification of the Efficiency of Time Segment Permutation in a Multilevel Optimization Method for Signal Ensembles. *Computer-integrated technologies: education, science, production.* Lutsk National Technical University. Lutsk. 2025. (№ 59), P.P. 303–312. https://doi.org/10.36910/6775-2524-0560-2025-59-38.

[11] Bershov, V., Yakymchuk N. The method of forming ensembles of complex signals based on multiscale decomposition of time intervals at different levels of detail. *Науковий журнал «Комп'ютерно-інтегровані технології: освіта, наука, виробництво». Телекомунікації та радіотехніка, Луцьк*, 2024. № 56, 2024. С. 325–334. https://doi.org/10.36910/6775-2524-0560-2024-56-39.

[12] Bershov V., Zhuchenko O. Adaptive method of forming complex signals ensembles based on multi-level recurrent time-frequency segment modeling. *Наукоємні технології*, № 3 (63), 2024. С. 257–264. https://doi.org/10.18372/2310-5461.63. 18953.

[13] Kasiselvanathan M., Palanisamy S., Sathishkumar N., Gurumoorthy K. B., Alshalali T. A. N., Narayanan S. L. Cross-correlation-based Signal Pruning Method (CCSPM) for Effective Signal Distortion Reduction in Massive MIMO Communications. Scientific Reports, 2025, Vol. 15, Article 20997. https://www.nature.com/articles/s41598-025-97403-7.

[14] Said M. R., Oppenheim A. V., & Lauffenburger D. A. Modeling cellular signal processing using interacting Markov chains. *IEEE Signal Processing Magazine*, 2010. 27(6), P.60–71. https://dsp-group. mit.edu/wp-content/uploads/2024/11/ModelingCellularSignal.pdf

[15] Chen, Z., Zhou, D., & Zio, E. Hidden Markov model with auto-correlated observations for degradation modeling of manufacturing systems. *Reliability Engineering & System Safety*, 2019. P. 224–234. https://doi.org/10.1016/j.ress. 2018.11.016.

Шевченко О. О., Лисечко В. П.

МЕТОД ЧАСОВИХ ПЕРЕСТАНОВОК НА ОСНОВІ МАРКІВСЬКИХ МОДЕЛЕЙ

У статті запропоновано метод перестановок на основі марковських моделей, призначений для оптимізації ансамблів складних сигналів у часовій області в умовах завад та стохастичної невизначеності. Особливістю методу є прогнозно-орієнтований вибір перестановок часових сегментів, який реалізується через марковське моделювання переходів між станами ансамблю сигналів. На відміну від відомих підходів, що орієнтуються лише на поточні значення взаємної кореляції, запропонований метод враховує прогнозовану динаміку ансамблю, що дозволяє мінімізувати ризик переходу до станів з підвищеною кореляцією та забезпечує стабільність часової структури сигналів.

У межах запропонованого методу сформовано множину можливих перестановок часових сегментів, для кожної з яких обчислюється математичне сподівання прогнозованого рівня взаємної кореляції та ентропійна міра невизначеності. Застосований інтегральний критерій оптимальності забезпечує узгоджену оцінку енергетичного балансу та структурно-часової впорядкованості ансамблю.

Введення коефіцієнта невизначеності β дозволяє регулювати баланс між швидкістю декореляції та стабільністю ансамблю: при $\beta \approx 0,15$ кількість переходів між станами зменшується на ≈ 60 % за мінімальної втрати точності прогнозу.

Експериментальні дослідження для широкосмугових систем при частоті дискретизації 10 МГц, показали зниження середнього коефіцієнта взаємної кореляції з 0,496 до 0,272 (≈ 45 %) і удосконалення інтегрального рівня бічних пелюсток (ISL) на ≈ 3 дБ. Показник спектральної рівномірності (SFM) збільшився з 0,67 до 0,83, що *свідчить про вирівнювання енергетичного розподілу та підвищення структурної узгодженості ансамблю сигналів. Доведено, що збіжність алгоритму досягається після 10–12 ітерацій.*

Таким чином, розроблений метод забезпечує адаптивну мінімізацію взаємної кореляції, стабілізацію енергетичних параметрів та підвищення завадостійкості ансамблів складних сигналів. Отримані результати свідчать про ефективність методу для застосування у когнітивних телекомунікаційних середовищах із множинним доступом і змінними умовами передачі.

Ключові слова: телекомунікації, перестановки, сигнал; SNR; оптимізація; кореляція; когнітивний, завадостійкість; марківська модель.

Shevchenko O., Lysechko V.

METHOD OF TIME PERMUTATIONS BASED ON MARKOV MODELS

The paper proposes a Markov-based permutation method designed to optimize ensembles of complex signals in the time domain under conditions of interference and stochastic uncertainty. The distinctive feature of the method is a forecast-oriented selection of time-segment permutations, implemented through Markov modeling of state transitions within the signal ensemble. Unlike conventional approaches that rely only on the current correlation level, the proposed method incorporates the predicted ensemble dynamics, allowing minimization of the risk of transition to highly correlated states and maintaining the temporal stability of signal structures.

Within the developed framework, a set of candidate permutations in the time domain is generated, for each of which the expected value of the predicted correlation and the entropy-based uncertainty measure are calculated. The integral optimality criterion provides a comprehensive assessment of the energy balance and structural-temporal coherence of the ensemble. Introducing the uncertainty coefficient β enables adaptive control of the trade-off between decorrelation speed and ensemble stability: at $\beta \approx 0{,}15$, the number of state transitions decreases by about 60 % with minimal loss in forecast accuracy.

Experimental studies performed for broadband communication signals with a sampling frequency of 10 MHz demonstrated a reduction of the average mutual correlation coefficient from 0,496 to 0,272 (≈ 45 %) and an improvement of the integrated side-lobe level (ISL) by ≈ 3 dB. The spectral flatness measure (SFM) increased from 0,67 to 0,83, confirming improved structural organization and temporal alignment of the ensemble. It was shown that algorithmic convergence is achieved within 10–12 iterations.

Thus, the developed method ensures adaptive minimization of mutual correlation, stabilization of energy parameters, and enhancement of interference immunity of complex signal ensembles. The obtained results confirm the effectiveness of the proposed approach for application in cognitive telecommunication environments with multiple access and dynamically varying transmission conditions.

Keywords: telecommunications; time permutation; signal; SNR; optimization; correlation; cognitive; interference immunity; Markov model.

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