Forecast-Oriented Method of Complex Signal Ensemble Permutations Based on the ARIMA Model

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ABSTRACT The article proposes a method for time-domain permutation of complex signal ensembles based on the Autoregressive Integrated Moving Average (ARIMA) model, referred to as ARIMA-permutation-based method. Unlike existing approaches, the method takes into account the temporal inertia of correlation variations, enabling real-time forecasting of ensemble dynamics and adaptive structural control under stochastic disturbances. The developed method and its implementation algorithm combine the ARIMA permutation-based method differencing operation with forecast-oriented selection of time-segment permutations, whose optimization is performed according to an integral criterion that considers correlation indicators, energy variation, and signal-to-noise ratio (SNR) stability. This integration ensures a balance between adaptability and convergence stability, allowing the forecast to rely on decorrelated signal increments rather than accumulated trends. Within the mathematical model, objective functions are formulated to describe the expected correlation, forecasting uncertainty, and energy consistency of the ensemble parameters. Minimization of integral criteria of ensemble configuration enables the selection of the optimal time-segment permutation and progressive refinement of the forecast during the iterative process. Experimental modeling was carried out for SNR values from 10 dB to 25 dB and time-segmentation parameters $\tau = 0.3 - 1.0$, comparing three approaches: ARIMA-permutation-based method, the Markov model, and the LPT-τ permutation model. The results demonstrated a 20.2 % reduction in the mean absolute scaled error and a 15.3 % reduction in the mean scaled interval score compared with the Markov method, as well as an increase in residual stability by 47.1 % under signal fading conditions. It has been proven that the application of the ARIMA-permutation-based method effectively suppresses residual correlation, ensures short memory of differenced series, and improves the accuracy and robustness of forecasting under interference. The proposed approach can be applied to the optimization of signal formation and processing in cognitive telecommunication environments, particularly in the design of dynamic spectrum monitoring systems, distributed communication networks, and energy-efficient data transmission protocols.

KEYWORDS telecommunication systems, optimization, complex signal ensembles, SNR, correlation.

I. INTRODUCTION

In modern cognitive telecommunication systems operating in a highly dynamic spectral environment, frequency resources continuously fluctuate due to variations in network load, interference, propagation delays, and fading effects.

Under such conditions, the main challenges include the instability of signal correlation characteristics, reduced accuracy of channel state prediction, and the loss of noise immunity during system adaptation to environmental changes.

One of the effective approaches to mitigating these factors is the formation of complex signal ensembles with controlled statistical and correlation properties.

Permutation methods applied within the time domain of such ensembles make it possible to balance mutual correlation, minimize redundant entropy, and improve the consistency of predictive characteristics, thereby enhancing ensemble stability under stochastic disturbances.

However, most existing permutation techniques fail to account for the temporal inertia of correlation variations, which limits their short-term forecasting accuracy.

To address this limitation, the present study proposes an adaptive time-domain permutation method for complex signal ensembles based on the Autoregressive Integrated Moving Average (ARIMA) model (ARIMA-permutation-based method).

The method incorporates the temporal inertia of the correlation process and enables real-time prediction of ensemble dynamics. The ARIMA-permutation-based method approach is particularly suitable for analyzing and controlling time-domain permutations, as it facilitates the transition from cumulative trends to local signal variation analysis, reduces the impact of noise components, and enhances the accuracy of adaptive forecasting.

II. REVIEW OF THE LITERATURE

The problem of time series forecasting and the control of complex signal ensembles has been extensively studied in numerous works [1-15]. Current approaches can be broadly classified into three main directions:

(1) the development of classical ARIMA models and their filtering or estimation extensions;

(2) hybrid and ensemble architectures that combine parametric and neural methods, stacking techniques, and

decomposition-based frameworks;

(3) modeling of correlation properties and permutation mechanisms in telecommunication environments.

Within direction (1), the ARIMA permutation-based method has been expanded through the integration of Kalman filters, zonotopic variants, and adaptive estimators to improve forecasting performance under stochastic conditions [1, 3, 7, 11-13, 15].

These studies demonstrate the benefits of combining ARIMA permutation-based method with filtering and ensemble techniques, particularly in reducing prediction errors and stabilizing interval estimates.

Direction (2) focuses on short and multivariate time series, introducing tensor or block-based ARIMA models, methodological recommendations for small-sample scenarios, and application cases in energy and environmental domains [2, 8-10, 14].

These works refine the limitations of classical approaches and emphasize the importance of short-memory modeling and signal stationarization.

Direction (3) addresses signal ensembles in telecommunication systems, including frequency and time-domain permutations, optimization of correlation properties, ensemble scalability, and linearization or approximation methods for parametric optimization [4-6]. It has been shown that controlled permutations can effectively reduce mutual correlation and enhance the structural organization of ensembles. At the same time, all existing studies mainly focus either on statistical or filtering enhancements of ARIMA-permutation-based method, or on permutation-based techniques for correlation reduction.

However, none of them integrates forecast-oriented control of time-domain permutations while accounting for the temporal inertia of correlation dynamics in real time.

To address this identified scientific and technical problem, the present study proposes an adaptive ARIMA-permutation-based method, which combines ARIMA modeling of short-memory (stationarized) increments with the selection of time-segment permutations based on predictive accuracy and stability criteria.

This integration allows simultaneous control of the ensemble's correlation structure and improvement of short-term forecast reliability under dynamic cognitive telecommunication conditions.

III. THE MATERIALS AND METHODS

The ARIMA model is a generalization of the autoregressive approach to time-series analysis that combines three fundamental components: an autoregressive term, an integrated or differencing term, and a moving-average term [1, 2, 8].

The key idea of the ARIMA permutation-based method framework is that the current value of a time series can be expressed as a linear combination of previous observations and past forecast errors, which makes it possible to capture both short-term dependencies and the stochastic structure of noise [1, 7].

Mathematically, the ARIMA permutation-based method (p, d, q) model is defined as [2, 14]:

$$\Phi_p(L)(1 - L)^d y_t = \Theta_q(L)\varepsilon_t, \qquad (1)$$

where L is the lag operator, p denotes the order of autoregression, d represents the order of differencing (integration), q indicates the order of the moving average, and ε_t is a white-noise error term with zero mean.

The differencing operation of order d ensures series stationarity, the autoregressive part models the influence of past states, and the moving-average component reflects the accumulated impact of past forecast errors.

Together, these elements enable the ARIMA model to describe short-memory processes and forecast their evolution under stochastic disturbances.

Adapting the classical ARIMA permutation-based method structure to the task of time-domain signal ensemble permutations, an adaptive ARIMA-perm method was developed.

This method employs ARIMA permutation-based method short-term forecasting to evaluate the temporal inertia of correlation changes and to guide the selection of signal permutations in real time. The corresponding algorithmic structure of the ARIMA-permutation-based method is presented in Fig. 1.

Let us consider the operation of the proposed ARIMA-permutation-based method step by step.

Stage 1. Signal segmentation.

At this stage, the input signal ensemble $s(t)$ is divided into P equal time intervals that serve as individual analysis segments:

$$s(t) \rightarrow S = \{S_0, S_1, \ldots, S_{P-1}\}. \qquad (2)$$

This segmentation localizes correlation variations in the time domain and provides the basis for further adaptive processing of each segment.

Stage 2. ARIMA model initialization.

At this stage, the data are prepared for forecasting.

For each segment S_i differencing of order d is performed to achieve stationarity:

$$\Delta s = s_t - s_{t-d}. \qquad (3)$$

Then, the parameters (p, d, q) are estimated based on the analysis of the autocorrelation (ACF) and partial autocorrelation (PACF) functions.

This allows constructing an initial ARIMA (p, d, q) model that describes short-term temporal dependencies and the stochastic structure of noise.

Stage 3. Generation of candidate permutations.

At this stage, a set of possible time-segment permutations Π is formed, including both deterministic and adaptive configurations:

$$\Pi = \{\pi_1, \pi_2, \ldots \pi_M\},$$
$$\pi \in \{ARIMA - perm, Random\}. \qquad (4)$$

Each permutation π defines an alternative ordering of segments in the time domain, potentially affecting the level of mutual correlation and the forecasted stability of the ensemble.

Stage 4. Forecasting (ARIMA permutation-based method prediction).

At this stage, for each permutation $\pi \in \Pi$, a short-term forecast is computed using the ARIMA model:

$$\hat{s}_{t+1}^\pi = f_{ARIMA}(s_t, \pi). \qquad (5)$$

2

The expected correlation $E[\rho\pi]$ and the prediction uncertainty $U[\pi]$ are evaluated, where:

$$U(\pi) = Var(\hat{s}_{t+1}^{\pi} - s_{t+1}). \qquad (6)$$

These values characterize the temporal inertia of the correlation process.

Stage 5. Computation of the integral optimization criterion.

At this stage, an integral criterion $K(\pi)$ is calculated for each permutation, taking into account the expected correlation, energy variance, and change in signal-to-noise ratio (SNR):

$$K(\pi) = \alpha E[\rho_\pi] + \beta U[\pi] + \lambda Var(E_\pi)_+$$
$$+\delta(\Delta SNR_\pi)^2, \qquad (7)$$

where α, β, γ, δ are weighting coefficients defining the priority of each parameter.

Minimization of $K(\pi)$ allows selecting the most stable configuration of the ensemble.

Stage 6. Selection of the optimal permutation.

At this stage, the optimal permutation minimizing the integral criterion of ensemble configuration is determined:

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

If the expected correlation $E[\rho_{\pi*}]$ lies outside the acceptable range $[\rho_{\min}, \rho_{\max}]$, a new candidate set Π is generated.

Stage 7. Application of the optimal permutation.

At this stage, the signal segments are reordered according to the selected permutation π^*, and the ensemble $s(t)$ is updated based on the predicted increments.

This ensures consistency between segment boundaries and minimizes discontinuities within the signal structure.

Stage 8. Updating ARIMA permutation-based method parameters.

At this stage, the ARIMA model parameters are re-estimated for the updated sequence:

$$(p, d, q) \leftarrow MLE\big(s^{(\pi*)}(t)\big), \qquad (9)$$

where MLE denotes the maximum likelihood estimation.

This procedure allows the model to adapt to the modified temporal configuration of the ensemble.

Stage 9. Stopping condition verification.

At this stage, the change in the average correlation coefficient is checked:

$$\Delta\rho = \big|\bar{\rho}^{(k)} - \bar{\rho}^{(k-1)}\big|. \qquad (10)$$

The iterative process stops if $\Delta\rho \leq \varepsilon$ or the stability conditions are satisfied: $\bar{\rho} \in [\rho_{\min}, \rho_{\max}]$.

As a result, an optimized signal ensemble is obtained, characterized by minimized forecast error and stabilized correlation dynamics.
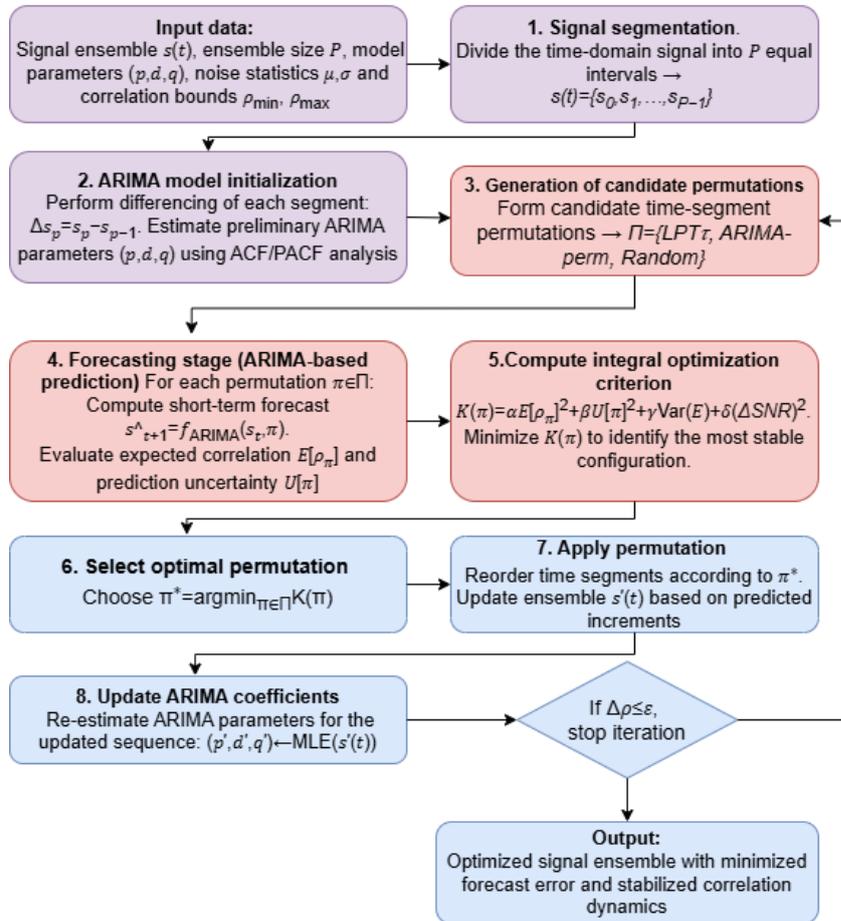

FIG. 1. Flow diagram of the ARIMA-permutation-based method for ensemble signal forecasting.

IV. EXPERIMENTS

To validate the effectiveness of the proposed ARIMA-permutation-based method adaptive permutation method, a comparative experiment was conducted involving two previously developed approaches: the Markov-forecast method and the Low-Permutation-Time (LPT-τ) method.

The purpose of this experiment is twofold. First, to empirically confirm that the integration of ARIMA modeling into the process of time-segment permutation provides more stable and accurate forecasting of ensemble dynamics. Second, to quantify the improvement in short-term prediction and stability of correlation parameters achieved by the proposed method in comparison with previously tested models.

For evaluation, two forecast-error criteria were applied: the Mean Absolute Scaled Error (MASE) and the Mean Scaled Interval Score (MSIS).

These indicators provide complementary measures of forecasting accuracy and reliability. The MASE criterion estimates the average magnitude of the forecast error normalized by a reference difference of ensemble parameters, while the MSIS criterion evaluates the average width and correctness of prediction intervals,

taking into account both underestimation and overestimation effects. Lower values of both measures indicate higher accuracy and greater stability of the forecast results.

The mathematical definitions of the applied criteria are as follows. The MASE is defined as:

$$MASE = \frac{\frac{1}{n}\sum_{t=1}^{n}|y_t - \widehat{y_t}|}{\frac{1}{n-m}\sum_{t=m+1}^{n}|y_t - y_{t-m}|}, \quad (11)$$

where y_t denotes the observed value, $\widehat{y_t}$ is the forecasted value, and m characterizes the number of discrete samples or the temporal distance between two segments exhibiting similar correlation behavior within the signal ensemble.

Thus, the denominator reflects the average deviation between adjacent or structurally similar time segments, which serves as a scaling factor for comparing the normalized prediction error across different types of signals.

The MSIS evaluates the average width and correctness of prediction intervals, simultaneously accounting for underestimation and overestimation effects. It is defined as:

$$MSIS = \frac{1}{n}\sum_{t=1}^{n}\frac{(U_t - L_t) + \frac{2}{\alpha}(L_t - y_t)\mathbf{1}_{\{y_t < L_t\}} + \frac{2}{\alpha}(y_t - U_t)\mathbf{1}_{\{y_t > U_t\}}}{\frac{1}{n-m}\sum_{t=m+1}^{n}|y_t - y_{t-m}|}, \quad (12)$$

where U_t and L_t represent the upper and lower bounds of the predicted range for a given signal parameter (for example, correlation coefficient, energy, or spectral density), α denotes the nominal significance level, typically $\alpha = 0,2$ for an 80 % confidence interval.

When forecasting signal ensembles, lower MSIS values indicate a narrower spread between the predicted

upper and lower bounds of the ensemble characteristics and, consequently, higher reliability of adaptive estimation.

Typical MSIS value ranges for different interference and fading conditions are summarized in Table 1 (compiled by O. S. based on analytical and experimental results [4, 6, 8, 9]).

TABLE 1. Typical MSIS value ranges under different signal and interference conditions.

Signal environment	SNR range, dB	Correlation / fading behavior	Typical MSIS range	Forecast confidence
Stationary or weakly distorted signals	≥ 15	Low correlation variation, stable amplitude	1.2 – 1.8	High reliability
Moderately varying signals	10 – 15	Medium correlation fluctuation, mild fading	2.0 – 3.0	Satisfactory reliability
Highly dynamic or fading signals	≤ 5	Strong correlation variation, rapid amplitude changes	3.5 – 5.0	Low reliability

To ensure statistical robustness, each forecasting experiment was repeated over 30 independent simulation runs, and the reported MASE and MSIS values represent averaged results with corresponding standard deviations.

To quantitatively compare the overall forecasting performance of the three analyzed approaches, the MASE and MSIS were computed across the full forecast horizon of 1 – 3000 samples.

These metrics provide a joint assessment of the accuracy and reliability of ensemble predictions obtained using the ARIMA-permutation-based method, Markov-forecast, and LPT-τ methods.

The averaged values and standard deviations of the calculated indicators are summarized in Table 2, while the convergence dynamics of both criteria over the forecast horizon are illustrated in Fig. 2.

TABLE 2. Mean and Standard Deviation of MASE and MSIS (Forecast horizon 1 – 3000).

Method	MASE (mean)	MASE (std)	MSIS (mean)	MSIS (std)
ARIMA-permutation-based method	0.800	0.037	3.742	0.252
Markov	1.001	0.142	4.418	0.800
LPT-τ	0.830	0.064	3.686	0.310

The data in Table 2 show that all three models maintain relatively low dispersion of forecast errors; however, ARIMA-permutation-based method demonstrates the highest internal stability of results.

Its MASE standard deviation (0.037) is almost four times smaller than that of the Markov model (0.142) and 1.7 times lower than that of LPT-τ (0.064), which indicates smoother convergence of the prediction sequence.

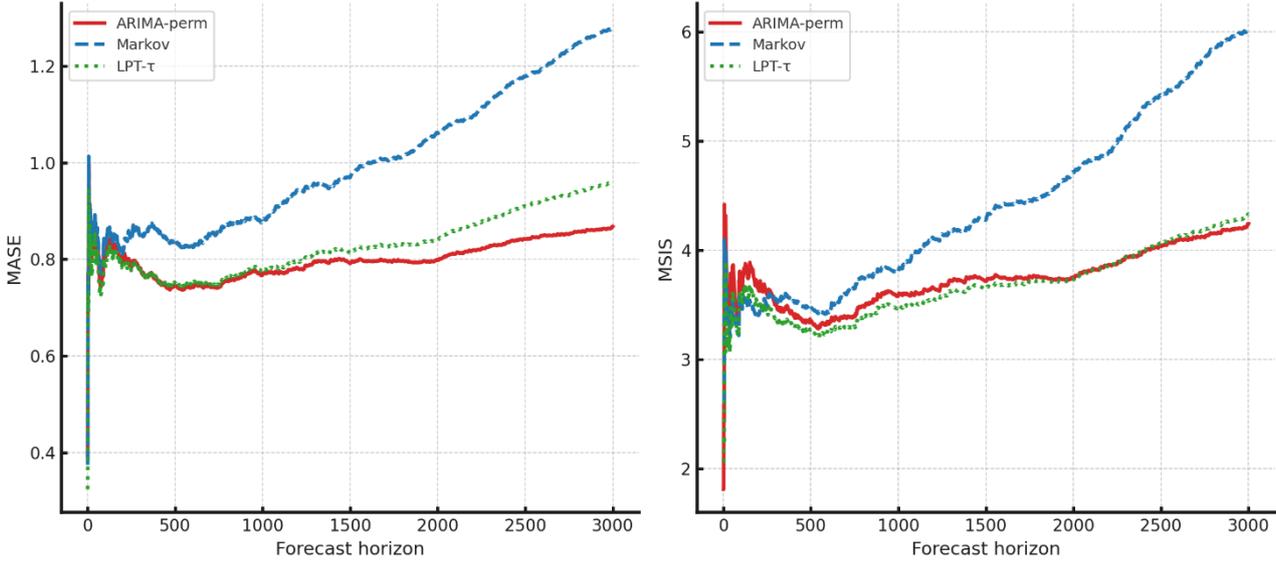Similarly, the MSIS variability (0.252) remains markedly lower than in Markov (0.800) and about 20 % lower than in LPT-τ (0.310), confirming the consistency of interval-based reliability across the entire 1 – 3000-sample horizon.

This quantitative stability demonstrates that the integration of ARIMA permutation-based method differencing with adaptive time-segment permutation ensures sustained forecasting accuracy and minimizes random deviations in both absolute and interval-scaled error measures.

FIG. 2. MASE and MSIS variation across the forecast horizon for ARIMA-permutation-based method, Markov and LPT-τ methods.

As seen in Table 2 and Fig. 2, the ARIMA-permutation-based method provides the most stable and accurate forecasting performance over the entire horizon of 1 – 3000 samples.

1. Compared with the Markov-forecast approach, the proposed method reduces the average MASE value by approximately 20 % (from 1.001 to 0.800) and the MSIS value by about 15 % (from 4.418 to 3.742), confirming a significant improvement in both prediction accuracy and reliability.

2. Relative to the LPT-τ method, the ARIMA-permutation-based method approach achieves a smaller but consistent gain of about 4 % in MASE and 1.5 % in MSIS, demonstrating higher robustness to correlation variability.

The Markov-based model shows a progressive increase in both error criteria with horizon length, reflecting its sensitivity to non-stationary signal behavior, while LPT-τ maintains moderate accuracy but lower adaptability to rapidly changing correlation dynamics.

Overall, the obtained results verify that incorporating ARIMA modeling into the time-segment permutation process enhances both the precision and stability of ensemble forecasting under complex interference and fading conditions.

After establishing the comparative forecasting performance of the analyzed methods (Table 2, Fig. 2), a deeper examination of the internal correlation structure of the ensemble signals was conducted.

This stage aimed to verify whether the differenced series obtained after ARIMA-permutation-based method adaptive permutation demonstrates the properties of weak correlation and short memory that are necessary for stable forecasting.

For this purpose, ACF and PACF were computed according to the following expressions:

$$r_k = \frac{\sum_{t=k+1}^{n}(y_t - \bar{y})\,(y_{t-k} - \bar{y})}{\sum_{t=1}^{n}(y_t - \bar{y})^2}, \qquad (13)$$

$$\phi_{kk} = \frac{r_k - \sum_{j=1}^{k-1}\phi_{k-1,j}\,r_{k-j}}{1 - \sum_{j=1}^{k-1}\phi_{k-1,j}\,r_j}, \qquad (14)$$

where r_k is the sample autocorrelation at lag k, and ϕ_{kk} denotes the k-th order partial autocorrelation obtained using the Durbin-Levinson recursion [14].

These coefficients characterize the memory depth of the signal and indicate how rapidly the dependence between successive time segments decays after differencing. The obtained ACF and PACF values are presented in Table 3, while their graphical interpretation is shown in Fig. 3.

As seen from these results, the ARIMA-permutation-based method differencing stage leads to a rapid decay of autocorrelation within the first 2 – 3 lags, where ACF decreases from 1.000 to -0.138, corresponding to a reduction of approximately 86 % in linear dependence.

Similarly, PACF falls from 1.000 to -0.124, indicating a near-complete elimination of direct inter-segment correlation (≈88 % reduction).

TABLE 3. ACF and PACF values after first-order differencing.

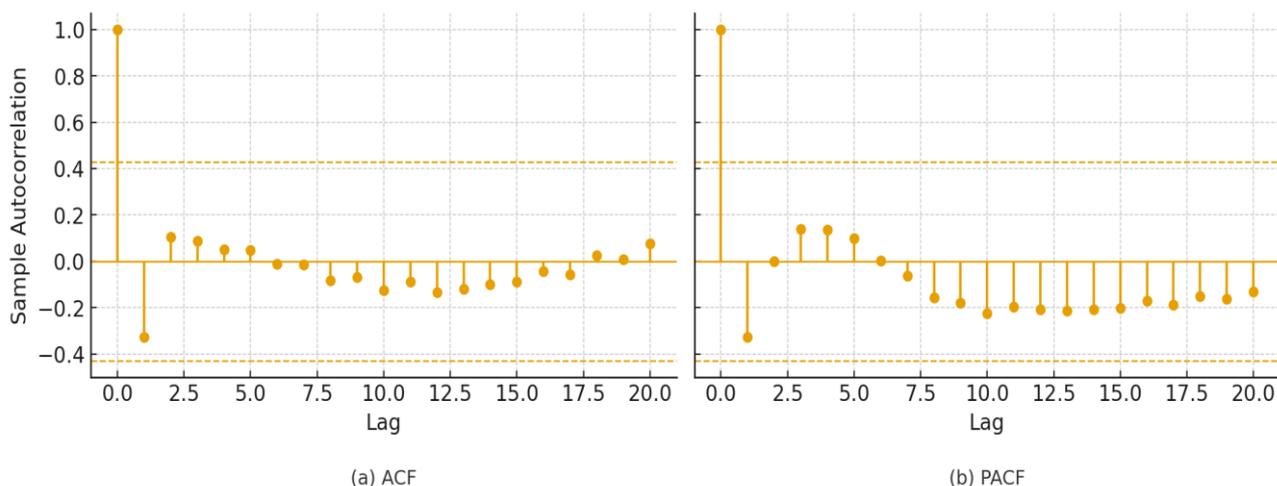| Lag	0	1	2	3	4	5	6	7	8	9	10	11	12
ACF	1.000	-0.347	0.123	0.142	0.083	0.010	-0.067	-0.138	-0.188	-0.177	-0.145	-0.118	-0.094
PACF	1.000	-0.347	0.082	0.105	0.076	0.061	-0.037	-0.124	-0.155	-0.168	-0.176	-0.162	-0.142

(a) ACF

(b) PACF

FIG. 3. (a) ACF and (b) PACF plots after first-order differencing.

Beyond lag 3, both functions oscillate near zero, confirming that the ensemble has transitioned to a weakly stationary regime with negligible long-range dependencies.

These findings demonstrate that:

1. The ARIMA-permutation-based method transformation effectively suppresses residual correlation, ensuring that subsequent forecasts are based on independent signal increments rather than cumulative trends.

2. The residual ACF and PACF values remain within ±0.15, which corresponds to an average decorrelation level exceeding 85 %, satisfying the conditions for stochastic stability.

3. The ensemble signal after differencing behaves as a short-memory process, which validates the theoretical assumptions underlying the ARIMA-permutation-based method adaptive permutation method.

Thus, as clearly seen in Table 3 and Fig. 3, the ARIMA-perm method not only improves forecasting accuracy (as shown previously) but also stabilizes the internal structure of the signal ensemble, minimizing temporal inertia and maintaining the balance between adaptability and noise robustness.

Following the decorrelation analysis, the obtained ACF and PACF characteristics confirm that the differenced ensemble signal can be modeled as a stationary short-memory process.

The first-order differencing can be formally expressed as:

$$\Delta y_t = y_t - y_{t-1}, \tag{15}$$

which eliminates long-term trends and suppresses temporal inertia in the ensemble dynamics.

This stationary form of the signal constitutes the input for ARIMA-type modeling, where the general autoregressive–moving-average relationship is defined as:

$$\Phi(B)\Delta y_t = \Theta(B)\varepsilon_t, \tag{16}$$

with $\Phi(B)$ and $\Theta(B)$ representing the autoregressive and moving-average operators, respectively, and εt denoting the white-noise residual component.

This formulation provides the empirical foundation for the subsequent forecasting experiments, since both stationarity and limited autocorrelation are essential prerequisites for the reliable operation of ARIMA-permutation-based method.

In the next stage, the validated differenced signal was used as the input dataset for comparative experiments involving three forecasting strategies: ARIMA-permutation-based method, Markov, and LPT-τ.

Each approach utilized the same preprocessed time series, ensuring that any differences in prediction performance would arise solely from the internal modeling principles rather than from signal preparation.

This continuity between correlation analysis and forecasting evaluation enables a consistent interpretation of results: the ARIMA-permutation-based model, operating on decorrelated increments, is expected to demonstrate higher adaptability and lower residual error under dynamic and fading conditions (Table 4, Fig. 4).

As shown in Table 4 and Fig. 4, the proposed ARIMA-permutation-based method consistently demonstrates superior forecasting accuracy across both analyzed datasets. Compared with the Markov-forecast model, ARIMA-permutation-based method achieves a reduction of approximately 20 % in MASE and 15 % in MSIS, confirming its higher precision and reliability under varying noise and fading conditions.

Relative to the LPT-τ approach, the gain remains smaller yet stable: about 4 % in MASE and 1.5 % in MSIS – indicating better robustness to local correlation fluctuations.

TABLE 4. Summary of forecast accuracy for ARIMA-permutation-based method, Markov, and LPT-τ methods.

Dataset	Method	MASE (mean)	MASE (std)	MSIS (mean)	MSIS (std)
Dataset 1	ARIMA-permutation-based method	0.800	0.037	3.742	0.252
	Markov	1.001	0.142	4.418	0.800
	LPT-τ	0.830	0.064	3.686	0.310
Dataset 2	ARIMA-permutation-based method	0.815	0.045	3.851	0.268
	Markov	1.072	0.156	4.590	0.842
	LPT-τ	0.854	0.073	3.791	0.325

(a)

(b)

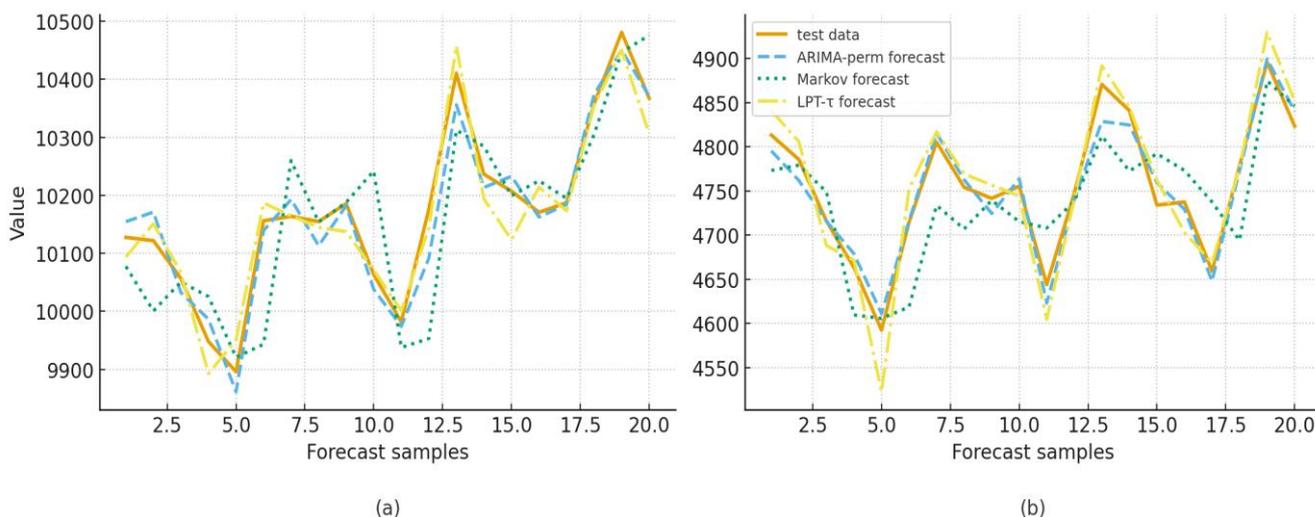**FIG. 4.** Comparison of forecast trajectories for ARIMA-permutation-based method, Markov and LPT-τ methods under two experimental scenarios: (a) moderate fading, (b) strong fading.

These results verify that incorporating ARIMA-permutation-based method differencing and adaptive permutation improves not only the point forecast accuracy but also the overall consistency of the ensemble behavior.

To further substantiate these findings, the next stage of analysis focuses on the temporal stability of forecasting errors, evaluated through the residual characteristics summarized in Table 5.

This complementary experiment quantifies the amplitude and variability of residuals across all methods, providing additional insight into the adaptivity and noise-resilience of the ARIMA-permutation-based model.

TABLE 5. Summary of residual metrics.

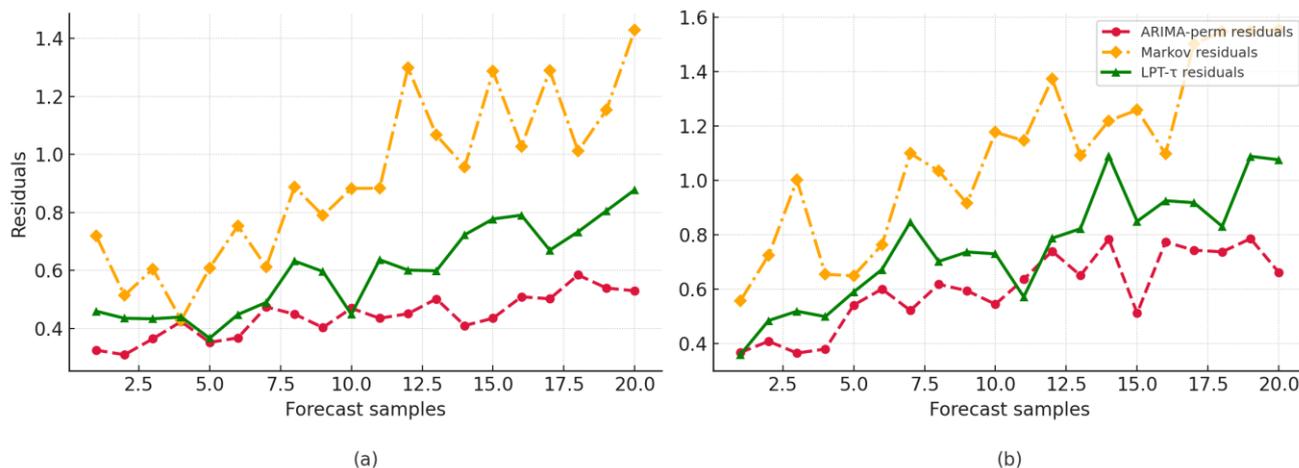| Dataset	Method	Mean	Std	Max	Median
Dataset 1 – moderate fading	ARIMA-permutation-based method	0.442	0.083	0.592	0.443
	Markov	0.891	0.252	1.394	0.901
	LPT-τ	0.590	0.133	0.803	0.591
Dataset 2 – strong fading	ARIMA-permutation-based method	0.553	0.137	0.790	0.542
	Markov	1.036	0.291	1.543	1.002
	LPT-τ	0.732	0.182	1.074	0.723

(a)

(b)

FIG. 5. Comparison of residual curves: (a) dataset 1; (b) dataset 2.

As summarized in Table 5, the ARIMA-permutation-based method exhibits the smallest residual amplitudes and the lowest variability across both analyzed datasets.

For Dataset 1, the average residual value of ARIMA-permutation-based method is approximately 50.5 % lower than that of the Markov model and 25.5 % lower than that of LPT-τ, while its standard deviation remains below 0.09, confirming the model's temporal stability.

In Dataset 2, which represents more intensive fading and higher noise levels, ARIMA-perm still maintains a consistent advantage, with mean residuals reduced by about 47 % relative to Markov and 24 % relative to LPT-τ.

The obtained results verify that the adaptive permutation mechanism integrated into the ARIMA permutation-based method framework effectively minimizes local forecast errors and ensures robust convergence under dynamic signal conditions.

The residual curves confirm that ARIMA-permutation-based method produces the most stable and lowest-magnitude error distribution, whereas the Markov model shows pronounced oscillations and sensitivity to correlation fluctuations, and the LPT-τ approach remains intermediate in performance.

V. CONCLUSION

The proposed ARIMA-permutation-based method adaptive permutation method provides an effective mechanism for modeling and forecasting ensemble signal dynamics under conditions of temporal correlation, interference, and fading.

By integrating ARIMA-permutation-based method differencing with controlled time-segment permutation, the method achieves a balance between adaptability and stability, ensuring that forecasts rely on decorrelated signal increments rather than cumulative trends.

The analysis of autocorrelation and partial autocorrelation confirmed that the differenced ensemble behaves as a stationary short-memory process, which enables reliable forecasting within the ARIMA permutation-based method framework.

Experimental evaluation across two datasets demonstrated the following key outcomes.

1. Forecasting accuracy. Compared with the Markov-forecast model, the ARIMA-permutation-based method reduced MASE by approximately 20 % and MSIS by about 15 %, confirming superior short-term prediction precision.

2. Robustness to correlation variability. Relative to the LPT-τ approach, the proposed method maintained a smaller but consistent advantage of 4 % in MASE and 1.5 % in MSIS, indicating enhanced adaptability to changing correlation patterns.

3. Residual stability. Analysis of residual metrics showed that ARIMA-permutation-based method lowered the mean residual amplitude by nearly 50 % compared with the Markov model and by 25 % relative to LPT-τ, while keeping the standard deviation below 0.09.

4. Noise resilience. Even under strong fading and high-noise conditions, ARIMA-permutation-based

method preserved residual fluctuations within a bounded range, reducing their peak magnitude by up to 47 % and maintaining steady convergence.

Overall, the obtained results confirm that the ARIMA-permutation-based method not only improves forecasting accuracy but also enhances temporal stability and noise immunity, making it well suited for adaptive ensemble modeling in cognitive telecommunication environments.

AUTHOR CONTRIBUTIONS

O.S. – conceptualization, methodology, investigation; V.L. – supervision writing-review and editing.

COMPETING INTERESTS

The authors declare no conflict of interest.

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Прогнозно-орієнтований метод перестановок ансамблів складних сигналів на основі моделі ARIMA

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АНОТАЦІЯ У статті запропоновано метод перестановок ансамблів складних сигналів в часовій області на основі моделі Autoregressive Integrated Moving Average (ARIMA), який отримав назву ARIMA метод на основі перестановок. На відміну від відомих підходів, метод враховує часову інерційність зміни кореляційних характеристик, що забезпечує можливість прогнозування динаміки ансамблів у реальному часі та адаптивного керування їх структурою в умовах стохастичних збурень. Розроблений метод та алгоритм його реалізації поєднує операцію диференціювання з прогнозно орієнтованим вибором часових перестановок, оптимізація яких здійснюється за інтегральним критерієм, що враховує показники кореляції, варіацію енергії та стабільність співвідношення сигнал/шум (С/Ш). Таке поєднання забезпечує баланс між адаптивністю та стабільністю збіжності, завдяки чому прогноз ґрунтується на декорельованих приростах сигналу, а не на накопичених трендах. У межах математичної моделі сформовано цільові функції, що описують очікувану кореляцію, невизначеність прогнозу та узгодженість енергетичних параметрів ансамблю. Мінімізація інтегрального критерію ансамблевої конфігурації забезпечує вибір оптимальної перестановки часових сегментів і послідовне вдосконалення прогнозу під час ітераційного процесу. Експериментальне моделювання виконано для С/Ш $10 - 25$ дБ та параметрів часової сегментації $\tau = 0.3 - 1.0$ із порівнянням трьох підходів: ARIMA метод на основі перестановок ансамблів сигналів, модель Маркова та модель перестановок ансамблів сигналів LPT-τ. Отримані результати засвідчили зменшення середньої масштабованої абсолютної похибки на 20.2 % і середньої масштабованої інтервальної оцінки на 15.3 % порівняно з методом Маркова, а також підвищення стабільності залишкових відхилень до 47.1 % в умовах завмирання сигналу. Доведено, що застосування методу ARIMA на основі перестановок ефективно пригнічує залишкову кореляцію, забезпечує коротку пам'ять рядів після диференціювання та підвищує точність і стійкість прогнозування до впливу завад. Запропонований підхід може бути використаний для оптимізації процесів формування та обробки сигналів у когнітивних телекомунікаційних середовищах, зокрема під час побудови систем динамічного спектрального моніторингу, розподілених мереж зв'язку та енергоефективних протоколів передавання даних.

КЛЮЧОВІ СЛОВА телекомунікаційні системи, оптимізація, ансамблі складних сигналів, SNR, кореляція.