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VOLOSHCHUK Andrii
Ternopil Ivan Puluj National Technical University
https://orcid.org/0009-0007-1478-1601
e-mail:andrii_voloshchuk3969@tntu.edu.ua
OSUKHIVSKA Halyna
Ternopil Ivan Puluj National Technical University
https://orcid.org/0000-0003-0132-1378
e-mail:osukhivska@tntu.edu.ua
KHVOSTIVSKYI Mykola
Ternopil Ivan Puluj National Technical University
https://orcid.org/0000-0002-2405-4930
e-mail:hvostivskyy@tntu.edu.ua
SVERSTIUK Andrii
Ternopil Ivan Puluj National Technical University,
I. Horbachevsky Ternopil National Medical University
https://orcid.org/0000-0001-8644-0776
e-mail: sverstyuk@tdmu.edu.ua

# APPLICATION OF PERIODICALLY CORRELATED STOCHASTIC PROCESSES FOR FORECASTING ELECTRICITY CONSUMPTION

*The article substantiates the application of the mathematical apparatus of periodically correlated stochastic processes (PCSP) for modeling and forecasting electricity consumption in power systems. The relevance of the research is determined by the need to improve the accuracy of energy load forecasting under conditions of complex temporal consumption structure with pronounced daily, weekly, and seasonal periodicity.*

*The aim of the work is to develop a new approach to energy load forecasting based on the energy theory of stochastic signals using the PCSP model. For the analysis, experimental data of hourly electricity consumption from a private household were used, aggregated at daily, weekly, and monthly scales.*

*A common-phase method for processing electricity consumption signals is proposed, both with and without consideration of cross-correlation relationships between components. It was established that the consumption correlation function demonstrates periodic behavior with a 24-hour period, with the daily harmonic accounting for 65-75% of the total signal energy.*

*The research results showed that the common-phase method with consideration of cross-correlation relationships ensures the detection of hidden patterns in the energy consumption structure and allows accounting for the inertia of power systems. The obtained correlation components can be used as informative features for load forecasting and training artificial intelligence models.*

*The practical significance of the work lies in creating a theoretical foundation for developing adaptive algorithms for energy consumption forecasting and their implementation in smart grid management systems.*

*Keywords: periodically correlated stochastic processes, electricity consumption forecasting, common-phase method, correlation components, power systems.*

ВОЛОЩУК Андрій, ОСУХІВСЬКА Галина, ХВОСТІВСЬКИЙ Микола
Тернопільський національний технічний університет імені І. Пулюя
СВЕРСТЮК Андрій
Тернопільський національний технічний університет імені І. Пулюя,
Тернопільський національний медичний університет імені І.Я. Горбачевського

# ЗАСТОСУВАННЯ ПЕРІОДИЧНО КОРЕЛЬОВАНИХ СТОХАСТИЧНИХ ПРОЦЕСІВ ДЛЯ ПРОГНОЗУВАННЯ СПОЖИВАННЯ ЕЛЕКТРОЕНЕРГІЇ

*У статті обґрунтовано застосування математичного апарату періодично корельованих стохастичних процесів (ПКСП) для моделювання та прогнозування споживання електроенергії в енергетичних системах. Актуальність дослідження зумовлена необхідністю підвищення точності прогнозування енергетичного навантаження в умовах складної часової структури споживання з вираженою добовою, тижневою та сезонною періодичністю.*

*Метою роботи є розробка нового підходу до прогнозування енергетичного навантаження на основі енергетичної теорії стохастичних сигналів з використанням моделі ПКСП. Для аналізу використано експериментальні дані погодинного споживання електроенергії приватного господарства, агреговані в добовий, тижневий та місячний масштаби.*

*Запропоновано синфазний метод обробки сигналів споживання електроенергії з урахуванням та без урахування взаємокореляційних зв'язків між компонентами. Встановлено, що кореляційна функція споживання демонструє періодичну поведінку з періодом 24 години, а на добову гармоніку припадає 65-75% загальної енергії сигналу.*

*Результати дослідження показали, що синфазний метод з урахуванням взаємокореляційних зв'язків забезпечує виявлення прихованих закономірностей у структурі енергоспоживання та дозволяє враховувати інерційність енергетичних систем. Отримані кореляційні компоненти можуть використовуватися як інформативні ознаки для прогнозування навантаження та тренування моделей штучного інтелекту.*

*Практичне значення роботи полягає у створенні теоретичної основи для розробки адаптивних алгоритмів прогнозування енергоспоживання та їх впровадження в системи управління розумними енергетичними мережами.*

*Ключові слова: періодично корельовані стохастичні процеси, прогнозування споживання електроенергії, синфазний метод, кореляційні компоненти, енергетичні системи.*

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## PROBLEM STATEMENT IN GENERAL TERMS

In the present context, modern power systems face numerous challenges caused by variations in energy consumption over daily and annual cycles, dependence on climatic factors, instability under extreme outages and blackouts, as well as the increasing complexity of energy infrastructure driven by the integration of smart grids, renewable energy sources, and other advanced technologies. Therefore, the investigation of novel approaches aimed at improving the accuracy of electricity consumption forecasting is of significant relevance.

Electricity consumption exhibits a complex temporal structure characterized by pronounced daily, weekly, and seasonal periodicity, combined with random fluctuations induced by various factors. Effective forecasting of such load dynamics is impossible without the application of adequate mathematical models that incorporate both regular, deterministic patterns and the stochastic nature of the process.

A variety of mathematical models for energy consumption analysis are known, including autoregressive models [1], neural networks [2, 3, 4], wavelet-based models, and other approaches. However, most of these do not account for the correlation relationships between different iterations of the same daily consumption realization, which prevents the tracking of phase–time variability dynamics for future load forecasting.The application of periodically correlated stochastic processes (PCSPs) in the energy sector are motivated by their ability to adequately represent the cyclic nature of electricity consumption variations driven by daily, weekly, and seasonal factors. This approach enables the construction of more accurate load forecasts, which, in turn, facilitate more efficient operational planning of power equipment, enhance the stability of power grid operation, and contribute to the reduction of technical losses.

The aim of this study is to employ novel approaches and methods designed to improve the accuracy of energy load forecasting and optimize energy resource management, utilizing the energy theory of stochastic signals, particularly models in the form of PCSPs and the corresponding processing tools.

## ANALYSIS OF PREVIOUS STUDIES AND PUBLICATIONS

In recent years, there has been an active development of new approaches to the mathematical modeling of complex systems [5], including the modeling of electricity consumption processes. Contemporary research focuses on mathematical modeling and statistical methods for processing measurement data in tasks related to electric load monitoring and assessing the characteristics of the normal operating modes of organizational electricity consumption [6]. Among the well-known approaches are the autoregressive-integrated moving average (ARIMA) models with time-independent parameters [7], as well as periodic autoregressive moving average (PARMA) models [8], which are characterized by deterministic parameter variations. Fundamental studies on cyclostationarity [9] have laid the theoretical foundation for understanding periodically varying statistical characteristics of signals. The application of various methods for electricity consumption forecasting is described in [10–14]. The use of artificial intelligence (AI) methods for energy allocation under electricity shortage conditions is discussed in [14], while a comprehensive review of load forecasting models employing AI is presented in [15].

A systematic analysis of existing methodologies has revealed that classical statistical models are not adapted to nonstationary and periodic changes in electricity consumption parameters, while machine learning technologies often lack transparency in their results and disregard the statistical nature of the process. The majority of existing approaches do not model the correlation relationships between different iterations of daily consumption realizations, which is crucial for tracking dynamic changes in the phase–time structure of energy loads with the aim of forecasting amplitude–time variations. Modern principles of time series forecasting with periodic components and methods for estimating continuous-time periodically correlated stochastic processes (PCSPs) are described in [15–18]. These approaches provide a comprehensive theoretical basis for the effective modeling and forecasting of energy processes with periodically varying characteristics.

The energy theory of stochastic processes, coherent covariance analysis of PCSPs, and the spectral theory of periodically correlated sequences have significantly advanced the mathematical apparatus applicable to electricity consumption forecasting. The theoretical foundation of this research lies in parameter estimation methods for periodically correlated stochastic processes [19, 20] and statistical methods for estimating probabilistic characteristics of models in the form of PCSPs [21].

Previous studies have demonstrated the suitability of PCSP-based models for analyzing various types of recurrent signals, including the simulation modeling of daily pulse signals in long-term monitoring systems. Therefore, the use of PCSP models is proposed for forecasting electricity consumption. The relevance of the proposed approach lies in applying the mathematical framework of periodically correlated stochastic processes to model electricity consumption, in particular using the in-phase method, which enables the comprehensive consideration of both periodic and stochastic components of consumption, as well as the modeling of complex correlation interactions between different values of daily realizations. This facilitates achieving high forecasting accuracy while preserving interpretability, supporting the analysis of dynamic changes in the phase–time structure of energy loads, and providing training data for AI models.

Moreover, the probabilistic approach in the form of PCSPs for analyzing and modeling stochastic signals ensures an optimal representation of the properties of energy systems by accounting for both regular deterministic patterns and random perturbations and noise, thereby enabling higher efficiency compared to existing methods.

An analysis of publications indexed in Scopus relevant to the use of PCSP models or studies related to forecasting loads in electric power systems demonstrates a considerable interest from the scientific community in this area (Fig. 1). However, the application of PCSPs for forecasting or analyzing electricity consumption in power grids has not been previously investigated.

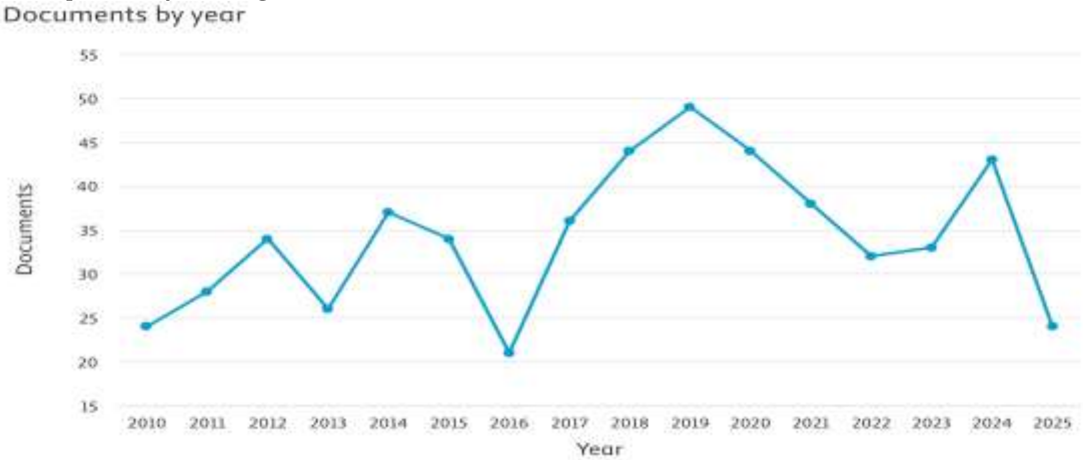



**Fig. 1. Research intensity on periodically correlated processes**

Recent studies demonstrate the applicability of the energy theory of stochastic signals, particularly periodically correlated stochastic processes (PCSPs), in the energy sector ranging from modeling daily load fluctuations in urban power grids to analyzing seasonal consumption trends in industrial complexes. In particular, research in recent years has shown that the PCSP approach can improve forecasting accuracy compared to traditional time series methods, which is critical for planning the operational modes of power equipment and minimizing electricity losses. This creates promising prospects for the development of this research direction, especially in the context of smart grids, where the accuracy of short- and medium-term electricity consumption forecasting is essential for the overall efficiency of the power system.

## MAIN MATERIAL OVERVIEW

To construct and validate the PCSP model, an hourly time series of electricity consumption was compiled from primary household meter readings. The data were aggregated into three temporal scales daily, weekly, and monthly for subsequent analysis. Figure 2 presents the overall electricity consumption pattern for the period from 15 January to 15 February 2025.

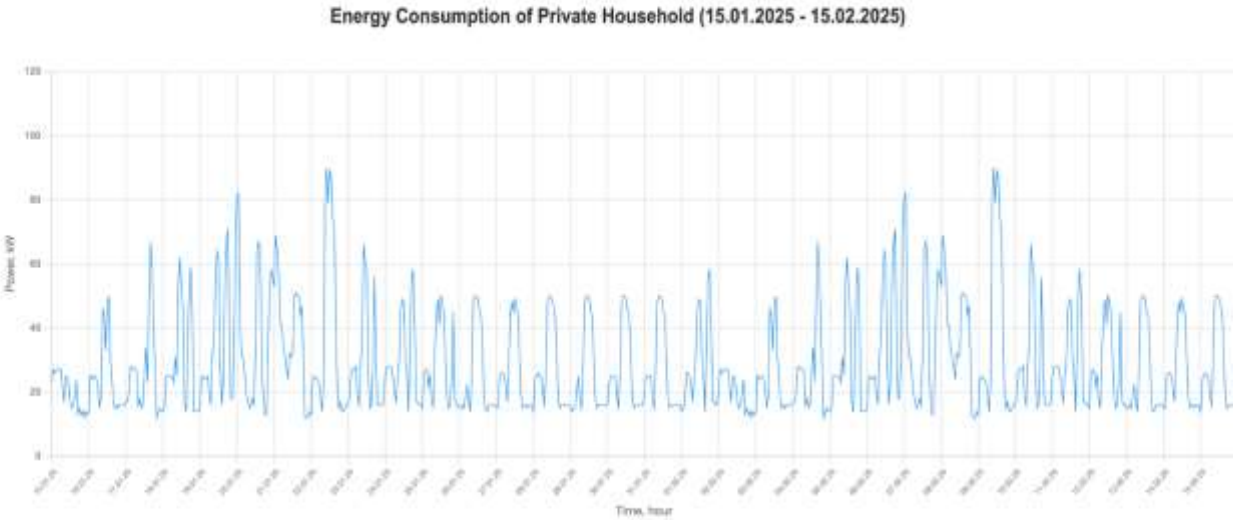



**Fig. 2. Electricity consumption of a private household during the period from 15 January 2025 to 15 February 2025**

The monthly electricity consumption graph exhibits characteristic daily fluctuations with pronounced load peaks and represents energy consumption as a function of time over a 720-hour interval. Regular daily oscillations are observed, with amplitudes ranging from 5 to 40 kWh. A clearly defined periodicity with peaks recurring every 24 hours reflects the natural rhythm of electricity usage and confirms the presence of stable daily activity cycles. Considering the above, the generalized model of the electricity consumption signal is expressed as an additive mixture in the form:

$$\xi(t) = \xi s(t) + \xi p(t), \tag{1}$$

where $\xi_s(t)$ – is the stochastic (variational) component of the daily electricity consumption signal;

$\xi_p(t)$ – is the periodic (daily) component of electricity consumption with period T, equal to the length of a day (24 hours).

The identified daily patterns $\xi_p(t)$ exhibit varying intensity $\xi_s(t)$ depending on the day of the week, which necessitated the analysis of weekly electricity consumption. The weekly period (Fig. 3) presents a complex picture of electricity consumption variations over a seven-day cycle, i.e., 168 hours, encompassing seven full days and revealing significant changes in the structure of electricity usage.

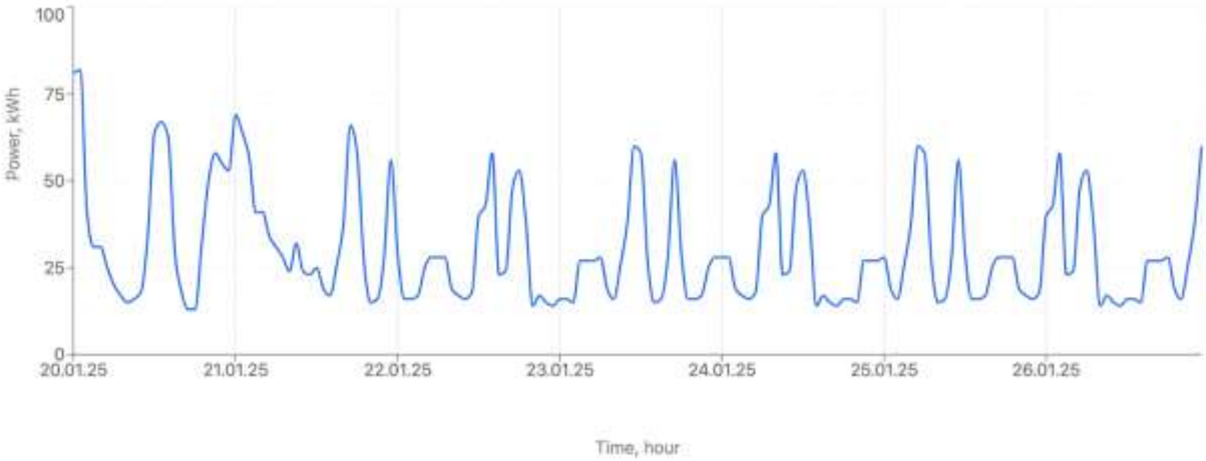



**Fig. 3. Weekly electricity consumption profile of a private household from 20 January 2025 to 26 January 2025**

The weekly electricity consumption profile from 20 January to 26 January 2025 also demonstrates the cyclical nature of consumption, with daily fluctuation intensities. A stable rhythm is established over the week daytime peaks alternate with nighttime troughs. The absence of significant reduction during the weekend (Saturday–Sunday) indicates a continuous technological process. The stable daily periodicity, with minimal differences between weekdays and weekends, the regular repetition of day–night cycles, and the lack of substantial "dips" during off-hours create highly predictable energy demand cycles, making the presented consumption profile particularly suitable for the application of PCSP mathematical models.

For detailed analysis of the daily consumption structure, a typical daily cycle was isolated, shown in Fig. 4, illustrating characteristic intraday electricity consumption patterns. The obtained data reveal distinctive daily fluctuations with pronounced load peaks. Notably, each day exhibits a pronounced peak in energy load characterized by daily variations in both timing and peak amplitude, corresponding to the principles of optimal energy system configuration.

The daily consumption profile for 15 January 2025 covers a full 24-hour cycle and displays characteristic amplitude variations. The observed pattern demonstrates stable periodicity with regular peak recurrence every 24 hours, reflecting natural rhythms of energy activity (Fig. 4). The daily cycle structure corresponds to a typical load distribution, with minimal base consumption during nighttime hours and a pronounced increase in energy consumption during daytime.

A comprehensive analysis of the experimental data at three levels of detail (monthly, weekly, and daily) confirms the presence of clearly defined periodic patterns in the structure of electricity consumption. The identified characteristics indicate a complex hierarchical structure of the consumption process, where daily cycles form the foundation, weekly variations reflect socio-economic factors, and monthly dynamics demonstrate the stability of recurring patterns. This multi-level periodicity of the investigated time series enables the application of the mathematical framework of periodically correlated stochastic processes (PCSPs), which effectively accounts for both deterministic periodic components and stochastic elements of the energy load.

When considering consumption within the framework of a stationary model, it is observed that the probability density functions transform over time, indicating a non-stationary realization of electricity consumption.

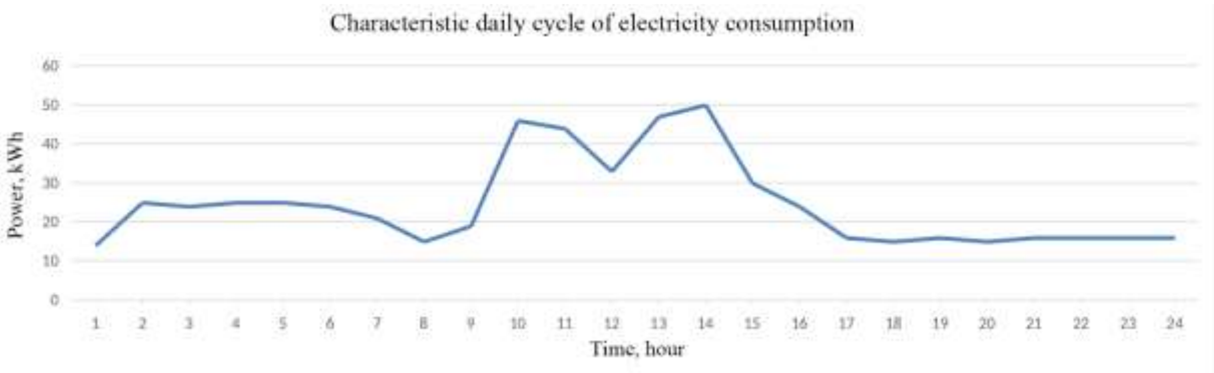



**Fig. 4. Implementation of the daily electricity consumption profile of a private household on 15 January 2025**

Correlation analysis of electricity consumption reveals that its correlation function, as an ensemble of realizations, is periodic and periodically vanishing as a continuous realization, indicating the iterative nature of the signal and its finiteness. Spectral analysis of electricity consumption realizations confirms the presence of a dominant frequency, f=1/24 Hz, which corresponds to the daily cycle. Additionally, harmonics at frequencies 2f and 3f were identified, representing intraday consumption peaks (morning and evening). Analysis of the spectral energy distribution shows that the daily harmonic accounts for 65–75% of the total signal energy, which justifies the selection of the correlation period Tk=24 hours.

Analysis of the electricity consumption structure indicates that each day is characterized by both random load fluctuations caused by unpredictable factors and regular daily patterns reflecting stable energy consumption rhythms. Electricity consumption belongs to the class of finite processes, as the realizations have clearly defined boundaries with a recurring structure. A key feature of the process is the presence of correlation links between different values of daily realizations, caused by the inertia of energy systems, consumer habits, and technological characteristics of energy equipment.

The probabilistic approach to the analysis and modeling of stochastic electricity consumption signals using the PCSP model allows for the description of energy system properties by accounting for both regular patterns and random influences, thereby enabling effective forecasting of future loads and optimization of energy resource distribution.

PCSPs generally combine the randomness of values with periodicity, interpreting it as the periodicity of probabilistic characteristics. This model allows for consideration of both deterministic and stochastic components, investigation of correlation relationships between different daily realizations, and analysis of the dynamics of changes in the phase–time structure of electricity consumption.

The mathematical expectation and correlation function of electricity consumption exhibit periodic behavior with a period Tk=24 hours, satisfying the fundamental conditions of periodically correlated stochastic processes (PCSPs). Traditional stationary models cannot adequately describe the periodic variations in electricity consumption parameters, while deterministic models fail to account for the stochastic nature of the process.

Compared to alternative approaches, PCSPs offer significant advantages. ARIMA models assume stationary of the process after differencing, which results in the loss of information about the periodic structure of electricity consumption. Although wavelet analysis allows for the detection of local signal features, it does not consider the correlation structure of the signal. Neural networks can approximate complex dependencies, but lack interpretability of results and do not account for the statistical nature of the process.

Therefore, the registerogram of the electricity consumption variation signal ξ(t) is interpreted as a realization of a PCSP and is expressed in the form:

$$\xi(t) = \sum_{k \in Z} \xi_k(t) e^{i\frac{2\pi k}{T}t}, \; t \in \mathbf{R}, \; k \in \mathbf{Z}, \tag{2}$$

where ξk(t) is the stochastic component of the signal structure, represented through stationary correlated processes (stationary components);

$e^{i\frac{2\pi kt}{T}}$ – periodic (cyclic) component of the signal with period parameter T;

*k* – index (number) of the stationary component.

The periodic component $\xi_k(t)$ in expression (2) reflects regular daily consumption patterns operating modes and the natural day–night cycle, whereas the stochastic component $e^{i\frac{2\pi kt}{T}}$ describes random deviations from the typical daily profile caused by meteorological conditions, unforeseen events, equipment failures, and other irregular factors. The model assumes the existence of inter-realization correlation links, which allows accounting for the inertial properties of the energy system and enables forecasting consumption based on previous daily cycles.

Representing the signal as a PCSP (1) justifies the application of known methods of synchronous processing (both considering and ignoring inter-component dependencies) and component-wise processing through estimation of probabilistic characteristics as informative features indicative of possible changes in electricity consumption.

The choice of the synchronous method of PCSP for electricity consumption analysis is motivated by a number of theoretical and practical advantages, making this approach appropriate for the task. The theoretical justification of the synchronous method's effectiveness is confirmed by its ability to optimally estimate PCSP parameters.

The synchronous method provides estimation/computation of predictive indicators in the form of correlation components of the centered signal based on parametric covariance statistics:

$$\hat{B}_k(u) = \frac{1}{T}\int_0^T \hat{b}_\xi(t,u)\exp\left(-ik\frac{2\pi}{T}t\right)dt \tag{3}$$

where $k$ - component index;
$u$ - time shift;
$\hat{b}_\xi(t,u)$ - parametric covariance:

$$\hat{b}_\xi(t,u) = \frac{1}{N}\sum_{n=0}^{N-1}\overset{0}{\xi}(t+u+kT)\overset{0}{\xi}(t+kT) \tag{4}$$

where ° denotes the centering operator.

The procedure for identifying the load level state of the energy system based on correlation components employs a criterion that is grounded on averaging component values over time shifts and components according to the following expressions:

$$M_k\left\{\hat{B}_k(u)\right\} = \frac{1}{K_{\max}}\sum_{k=1}^{K_{\max}}\hat{B}_k(u), \quad u=\overline{1,U_{\max}},\ k=\overline{1,K_{\max}}. \tag{5}$$

$$M_u\left\{\hat{B}_k(u)\right\} = \frac{1}{U_{\max}}\sum_{u=1}^{U_{\max}}\hat{B}_k(u), \quad u=\overline{1,U_{\max}},\ k=\overline{1,K_{\max}}. \tag{6}$$

where $k$ – index of the correlation component;
$u$ – time shift;
*Umax* – maximum length of time shift;
*Kmax* – the maximum number of components equals the number of discrete samples within the period.

Estimates of the correlation components (2) and their averaged realizations (4–5), obtained via the synchronous method, are unbiased and asymptotically efficient, ensuring high accuracy in modeling and forecasting. This is particularly important for energy systems, where forecasting errors can result in significant economic losses.

Statistic (2) enables the detection of hidden periodic patterns in the energy consumption structure that cannot be captured by classical time series analysis methods. The correlation components (2) convey information about the interrelations between different phases of the daily cycle, which is critical for accurate forecasting. The synchronous method without accounting for cross-correlation links provides a baseline analysis of the periodic structure of the process, revealing the main daily patterns. The enhanced method — which incorporates cross-correlation links — allows modeling complex dependencies among different daily realizations, reflecting the inertia of energy systems and consumer habits.

Figure 5 presents the results of applying synchronous analysis without (a) and with (b) consideration of cross-correlation links in averaging over components and time. This approach facilitates the identification of key periodic regularities in electricity consumption.

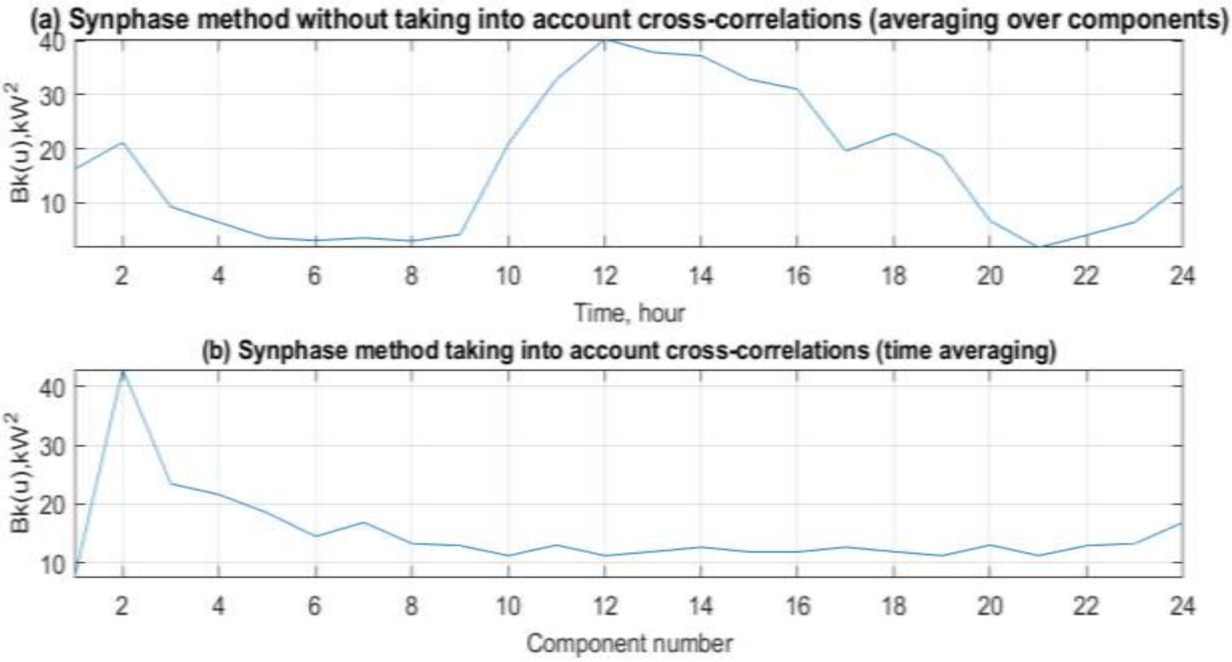



**Fig. 5. Results of common-phase analysis a) Synphase method without cross-correlations (component averaging) b) Synphase method with cross-correlations (time averaging)**

Figure 5 provide results of common-phase analysis using the Synphase method, comparing configurations without and with consideration of cross-correlations, based on component and time averaging respectively.

In the configuration without cross-correlations, the distribution of energy consumption is shown across hours of the day (1–24). The daily load profile exhibits clear periodicity, with oscillation amplitudes ranging from approximately 5 to 40 kW²·h. Minimum values (~5–7 kW²·h) occur during early morning hours (6–8 AM), corresponding to low consumer activity, while the peak (~40 kW²·h) is observed around midday (12–1 PM), corresponding to maximum energy demand.

In the configuration with cross-correlations, the results are presented as a function of component number (1–24). The energy contribution is dominated by the first few components (up to ~42 kW²·h for the first component), with subsequent components showing significantly lower and more stable values, indicating that most of the variance is captured by the leading modes.

Figure 6 illustrates the results of the enhanced common-phase analysis using the Synphase method, accounting for cross-correlations. The upper plot shows the temporal dynamics of the correlation function Bk(u), kW², averaged over components, across a 24-hour period. The values rapidly decline from a peak of ~20 kW²·h at hour 1 to ~5 kW²·h by hour 4, followed by stabilization at ~2–3 kW²·h. This indicates a strong initial autocorrelation effect that diminishes over time but remains present at a lower level.

The lower plot presents the distribution of the time-averaged correlation function across components. The values range from 1.5 to 4.5 kW²·h, with local maxima at the extreme components (~4.5 kW²·h) and a minimum in the central region (~1.7 kW²·h). This pattern reflects the complex interplay between system elements, where edge components exhibit higher correlations compared to the core.

By incorporating cross-correlation relationships, the Synphase method reveals hidden patterns and internal dependencies within the energy consumption structure. This enhanced approach provides a more accurate representation of system dynamics, offering a robust foundation for improving forecasting accuracy and optimizing energy resource management.

To further investigate the spatial-temporal structure of energy consumption, a three-dimensional representation of the common-phase analysis was conducted without accounting for cross-correlation relationships. The results, illustrated in Figure 7, provide a detailed visualization of the energy load dynamics through two complementary approaches: a 3D surface plot and a spectrogram.

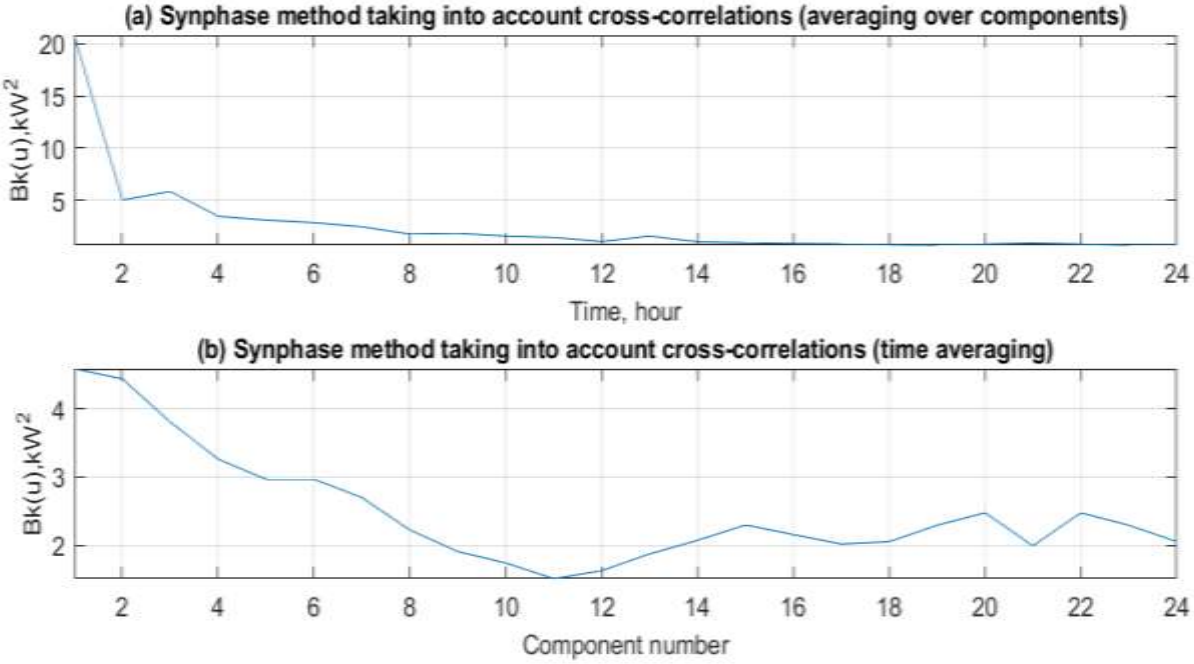
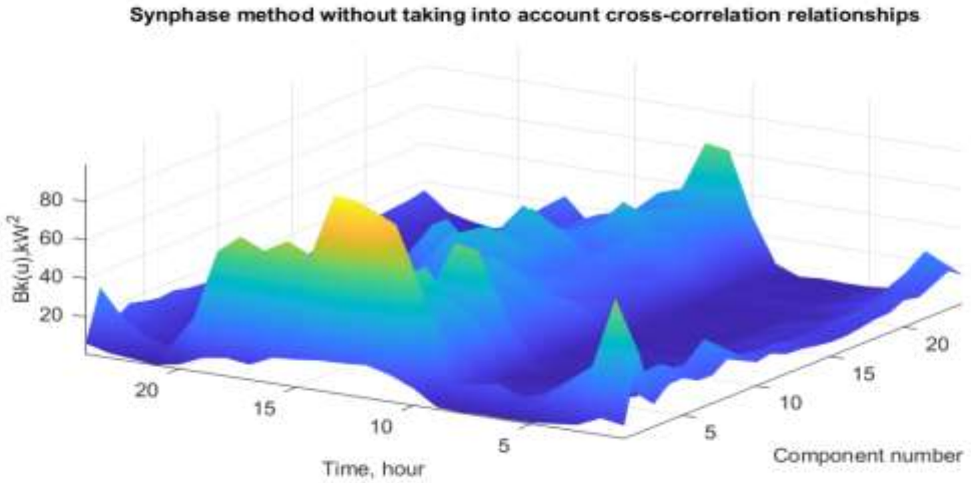
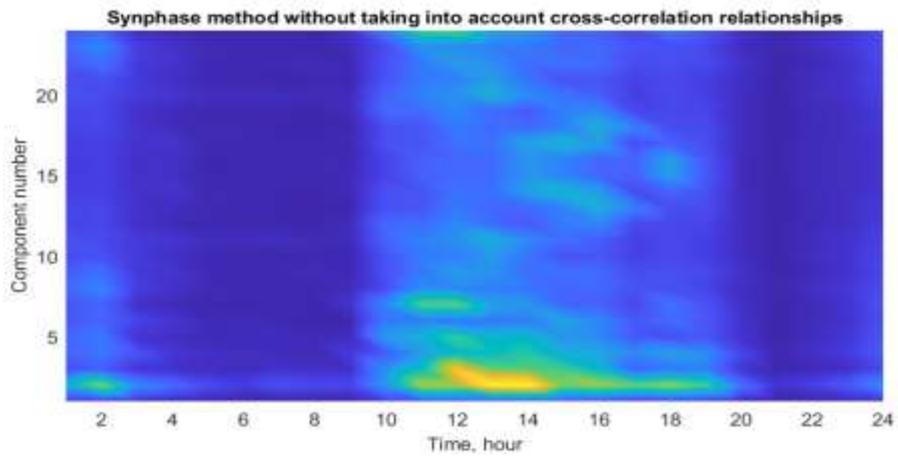



**Fig. 6. Results of common-phase analysis a) Synphase method without consideration of interrelationships (averaging over components) b) Synphase method with consideration of interrelationships (averaging over time)**




**(a)**




**(b)**

**Fig. 7. Three-dimensional representation of synchronous analysis without accounting for cross-correlation links a) 3D surface b) - spectrogram**

The 3D surface plot (Figure 7a) reveals a complex spatial-temporal structure of energy consumption, characterized by prominent peaks reaching ~80 $kW^2 \cdot h$. These peaks are particularly pronounced during hours 5–7 and 14–16, indicating periods of heightened energy demand. The surface elevation effectively captures the dynamic variations in energy consumption, highlighting how load intensity fluctuates across both time and component dimensions.

The spectrogram (Figure 7b) complements this analysis by providing a color-coded intensity map of the correlation function. The color gradient, ranging from blue (low intensity) to yellow (high intensity), represents the magnitude of Bk(u), $kW^2$. The most intense regions (yellow-green areas) are concentrated around hours 10–14, aligning with the peaks observed in the 3D surface plot. Additionally, the spectrogram reveals a gradual transition in energy load intensity, with lower values (dark blue) dominating the early morning and late evening hours. This pattern underscores the temporal evolution of energy consumption and its distribution across different components.

Together, these visualizations facilitate a comprehensive understanding of electricity consumption dynamics, uncovering hidden patterns and spatial interrelationships among load characteristics. The multidimensional approach adopted here offers insights that are not discernible through traditional one-dimensional analysis methods, thereby enhancing the accuracy of energy forecasting and resource management strategies.

The synchronous analysis representation (Fig. 5) allows analysis of the temporal evolution and component structure of the process, whereas the three-dimensional visualization reveals spatial interrelationships among various load characteristics. This multidimensional analysis is impossible to achieve using traditional one-dimensional methods.

Figure 8 presents the results of the common-phase analysis using the Synphase method, explicitly accounting for cross-correlation relationships. This approach enhances the accuracy of energy load modeling by capturing interdependencies between different system components.

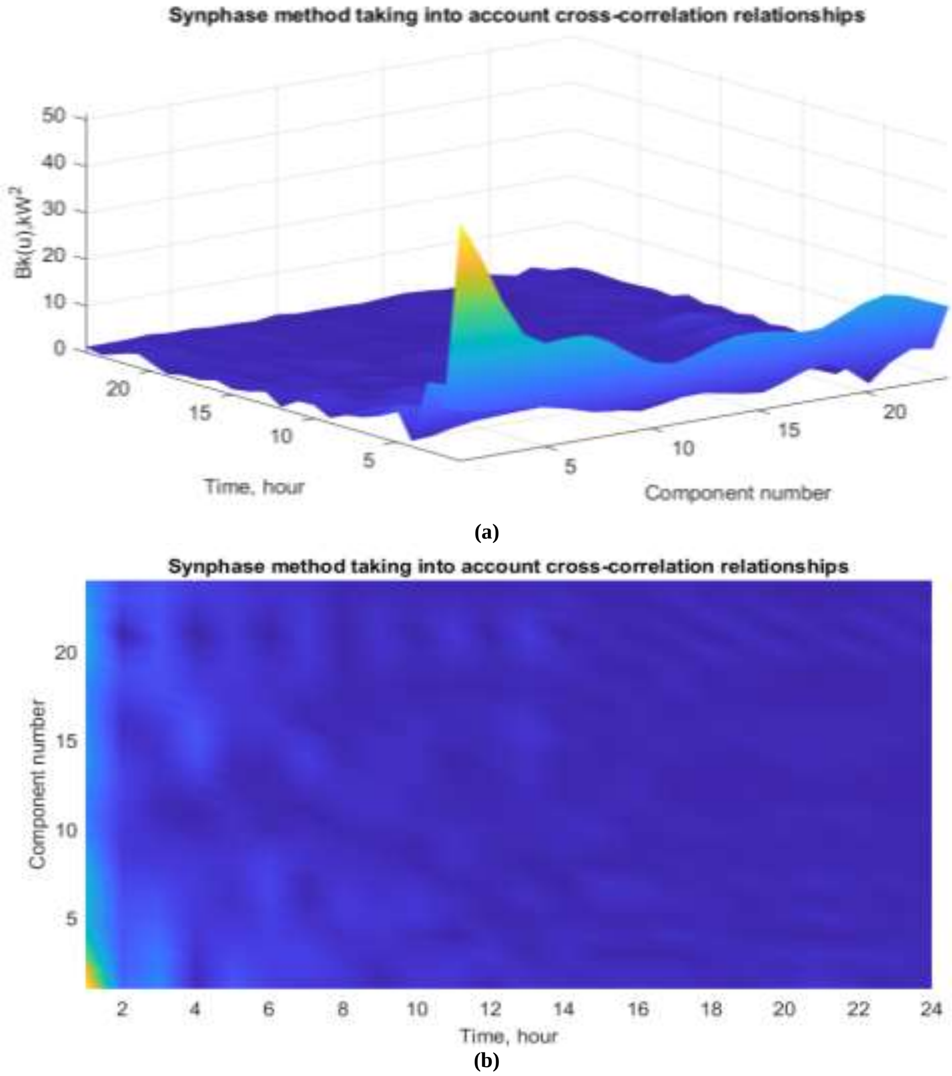



**Fig. 8. Common-phase method analysis accounting for cross-correlation links**
**(a) - three-dimensional view (b) - spectrogram**

In the three-dimensional view (Figure 8a), the correlation function demonstrates a noticeably smoother distribution compared to the analysis presented in Figure 7. Peak values are significantly reduced, reaching a maximum of approximately 50 $kW^2 \cdot h$, and the energy distribution appears more uniform across the entire time-component space. This indicates that incorporating cross-correlation relationships contributes to system stabilization by reducing extreme fluctuations in energy consumption.

The spectrogram (Figure 8b) further supports these findings. The color distribution is more homogeneous compared to Figure 7b, with predominantly lower-intensity regions (darker blue) suggesting a reduction in sharp variations. This confirms that accounting for cross-correlation links results in a more balanced energy load distribution across both time and components.

The analysis of variational correlations in electricity consumption provides a robust framework for the a priori determination of energy resource operating modes, facilitating optimization for high-quality power supply to consumers. Compared to the baseline method, this approach demonstrates superior modeling capabilities, offering improved accuracy for practical implementation in smart grid systems.

Key practical advantages of the synchronous method include computational efficiency and real-time implementation capability, making it suitable for integration into modern smart grid management systems where rapid processing of large data volumes is essential. Thus, the synchronous method represents an optimal tool for analyzing electricity consumption as a periodically correlated stochastic process (PCSP), practical efficiency, and high accuracy in modeling complex energy processes.

## CONCLUSIONS

This study substantiates the use of periodically correlated stochastic processes (PCSP) as an adequate mathematical model for forecasting electricity consumption. The application of the synchronous analysis/processing method, both with and without accounting for cross-correlation links, enables effective analysis and prediction of energy load based on correlation component values and their averaged realizations.

It has been established that the synchronous method incorporating cross-correlation links provides more accurate modeling of electricity consumption by considering complex correlation dependencies among various components of the energy load. The investigation of variational correlations of electricity consumption across different observation days provides a procedure for the a priori determination of energy resource operating regimes to optimize them for ensuring high-quality power supply to consumers.

Further research will focus on developing adaptive forecasting algorithms based on PCSP models and their implementation in smart grid management systems.

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