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ANALYSIS OF ELECTRICITY CONSUMPTION USING THE COMPONENT METHOD OF PERIODICALLY CORRELATED RANDOM PROCESSES

Contemporary energy systems, considering the diverse challenges emerging within energy infrastructure, require advanced analytical methodologies for electricity consumption forecasting. Traditional statistical approaches prove insufficient for modeling dynamic multi-scale temporal structures of electricity consumption signals aimed at predicting electrical loads in residential households.

This research presents a comprehensive approach to electricity consumption analysis utilizing the mathematical framework of periodically correlated random processes (PCRP), specifically employing the component method. The mathematical foundation of the methodology consists in representing electricity consumption signals as PCRP models with decomposition into constituent elements: deterministic trend components, periodic components of cyclical variations, and stochastic components of random deviations. Component analysis enables the identification of latent consumption patterns through decomposition of periodic characteristics. Therefore, the proposed method allows for the elimination of limitations inherent in traditional stationary models.

Empirical validation was conducted using a comprehensive dataset of residential electricity consumption spanning the period from July to August 2025. Experimental data demonstrated pronounced repetitive characteristics with systematic daily periodicity, confirming the theoretical premise regarding daily component dominance. Three-dimensional visualization of results revealed complex interaction dynamics between different frequency components of electrical load signals. Spectral analysis exhibited characteristic distribution with maxima for low-frequency components corresponding to daily harmonics.

The obtained results can be utilized for residential electrical load forecasting and enable both short-term and medium-term energy consumption predictions. This is significant not only for forecasting residential electrical loads, but also for optimizing electrical energy resources and managing intelligent networks.

Keywords: electricity consumption, mathematical modeling, forecasting, periodically correlated random processes, component analysis method.

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АНАЛІЗ СПОЖИВАННЯ ЕЛЕКТРОЕНЕРГІЇ З ВИКОРИСТАННЯМ КОМПОНЕНТНОГО МЕТОДУ ПЕРІОДИЧНО КОРЕЛЯЦІЙНИХ ВИПАДКОВИХ ПРОЦЕСІВ

Сучасні енергетичні системи, враховуючи різноманітні виклики, які виникають в енергетичній інфраструктурі, потребують удосконалених аналітичних методологій з метою прогнозування електроспоживання. Традиційні статистичні підходи є недостатніми для моделювання динамічних багатомасштабних часових структур сигналів електроспоживання з метою прогнозування електронавантаження приватного господарства.

Дослідження представляє комплексний підхід до аналізу електроспоживання з використанням математичного апарату періодично корельованих випадкових процесів (ПКВП), зокрема компонентного методу. Математична основа методології полягає у представленні сигналів електроспоживання як моделі у вигляді ПКВП з розкладом на складові елементи: детерміністичні трендові компоненти, періодичні компоненти циклічних варіацій та стохастичні компоненти випадкових відхилень. Компонентний аналіз забезпечує виявлення прихованих патернів споживання через розкладання періодичних характеристик. Тому запропонований метод дозволяє усунути обмеження традиційних стаціонарних моделей.

Емпірична валідація проведена на базі комплексного набору даних електроспоживання приватного господарства за період з липня по серпень 2025 року. Експериментальні дані продемонстрували виражені повторювані характеристики з систематичною добовою періодичністю, підтверджуючи теоретичну передумову щодо домінування добової компоненти. Тривимірна візуалізація результатів продемонструвала складну динаміку взаємодії між різними частотними компонентами сигналів електричного навантаження. Спектральний аналіз показав характерний розподіл з максимумами для *низькочастотних компонент, що відповідають добовим гармонікам. Отримані результати можуть бути використані при прогнозуванні електричного навантаження приватного господарства і дозволить здійснити як короткострокові, так і середньострокові прогнози енергоспоживання. Це є важливим не лише для прогнозування електронавантажень приватних господарств, але і для оптимізації електроенергетичних ресурсів, а також для управління інтелектуальними мережами.*

Ключові слова: електроспоживання, математичне моделювання, прогнозування, періодично корельовані випадкові процеси, компонентний метод аналізу.

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Introduction

Contemporary energy infrastructure has evolved into intricate, multi-layered networks that demand sophisticated analytical frameworks for load prediction and consumption modeling, with increasing emphasis on energy efficiency optimization [1]. Traditional forecasting methodologies prove insufficient when addressing the stochastic variability and dynamic behavioral patterns inherent in modern electrical grids [2]. Current energy consumption profiles exhibit distinctive characteristics, including recurring temporal patterns spanning daily, weekly, and seasonal intervals, interwoven with unpredictable fluctuations [3].

These irregular variations stem from evolving consumer habits and the inherent volatility of renewable energy sources, necessitating analytical approaches that seamlessly integrate deterministic modeling with stochastic assessment techniques. Modern electrical loads demonstrate unprecedented complexity through their dynamic, nonlinear, and multi-dimensional nature [4].

The scientific community has shown increasing interest in energy efficiency and component-based methodologies, as evidenced by comprehensive bibliometric analysis conducted using the Scopus database. Research focusing on energy systems has experienced remarkable expansion, with publication volumes increasing from approximately 50 documents in 2015 to over 230 in 2024, representing more than a four-fold increase according to Scopus bibliographic database analysis (Figure 1). This upward trajectory demonstrates the field's critical importance and active development within the research landscape.

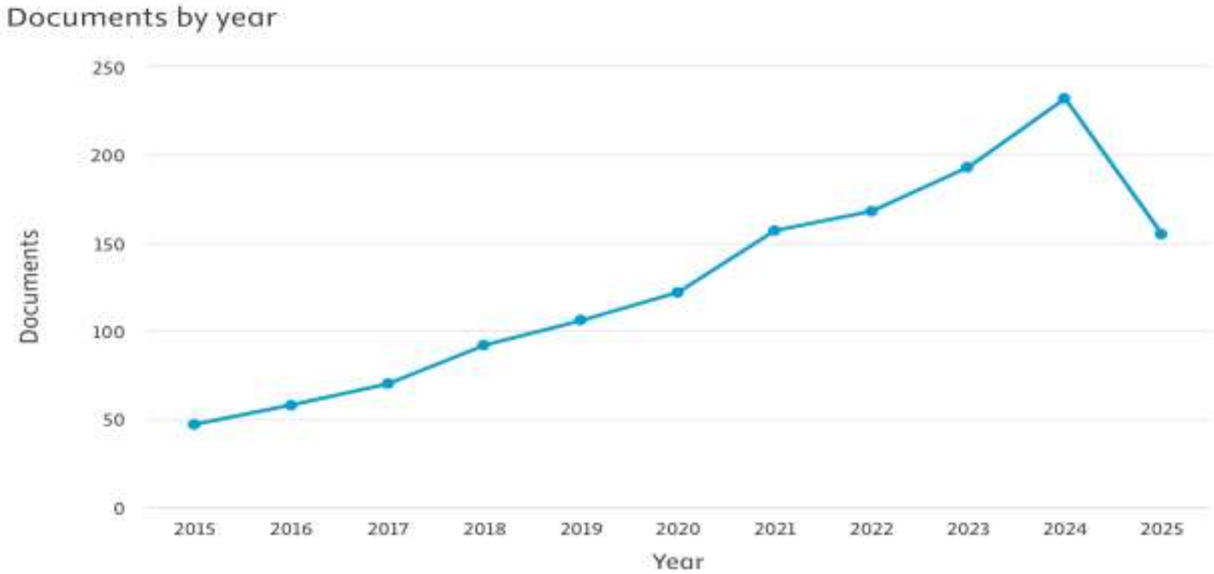

Fig. 1. Annual publication volume in energy efficiency and component analysis research (Scopus, 2015-2025)

Notably, computer science represents one of the most prominent subject areas in this domain, accounting for 11.9% of all publications according to Scopus bibliometric data, which underscores the relevance and significance of computational approaches like the one presented in this work (Figure 2). The interdisciplinary nature of energy research is further highlighted by substantial contributions from engineering (24.3%) and energy-specific studies (18.4%), creating a robust foundation for cross-disciplinary methodological development.

The fundamental approach centers on disaggregating aggregate load profiles into constituent elements: trend components representing long-term consumption trajectories, periodic elements capturing cyclical variations across multiple temporal scales, and stochastic components accounting for random deviations from expected patterns [5]. Component analysis techniques applied to electrical consumption data, through the representation of energy loads as periodically correlated stochastic processes, facilitate the extraction of latent consumption patterns and enable the development of adaptive forecasting models with superior precision [6, 7]. This methodology supports efficient data structuring, identification of consistent usage behaviors, and enhanced accuracy in energy resource planning [8].

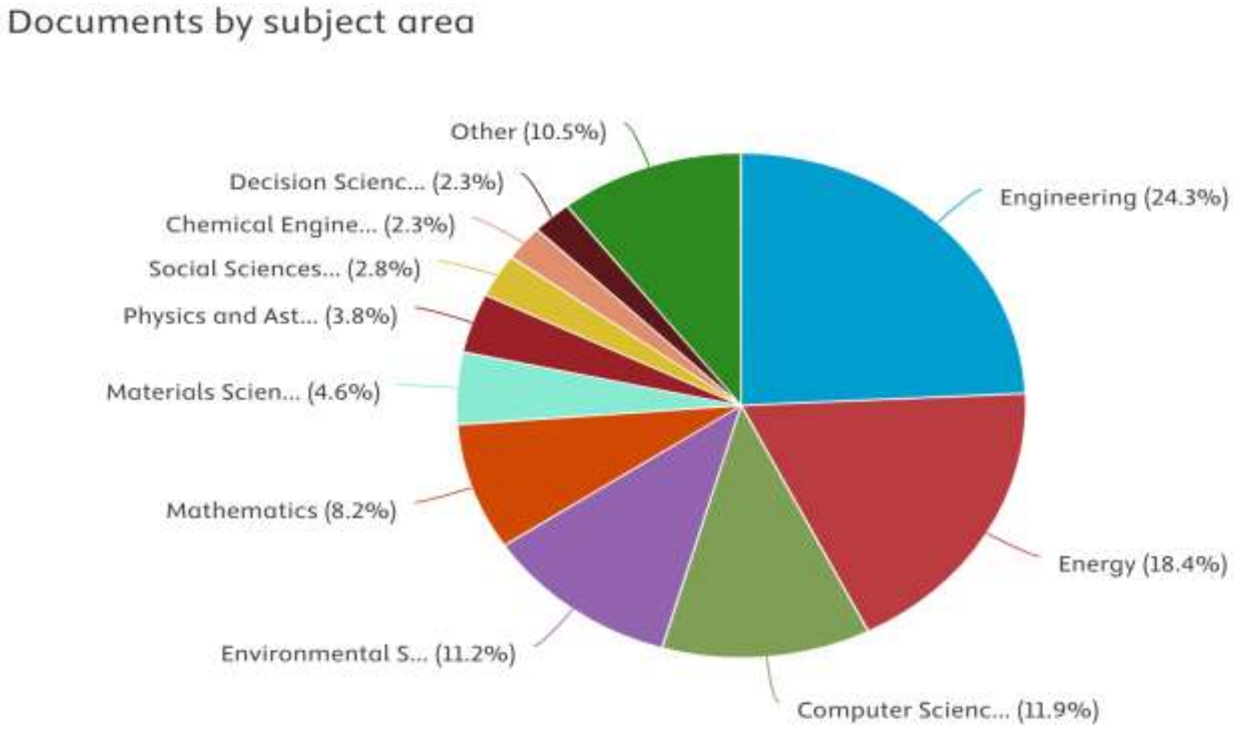

Fig. 2. Distribution of energy research publications by subject area according to Scopus bibliometric data

Analysis of the latest research and publications

Energy system modeling methodologies can be systematized into three fundamental paradigms: conventional statistical frameworks, machine learning architectures, and integrative hybrid solutions. Each paradigm presents distinct computational advantages while exhibiting inherent constraints when addressing the multifaceted nature of energy consumption dynamics.

Conventional statistical frameworks operate under the fundamental premise of temporal stationarity within observed data sequences [9]. Autoregressive Integrated Moving Average (ARIMA) methodologies, extensively utilized for near-term load prediction, require data transformation through differencing operations to achieve stationarity - an assumption frequently violated by the intrinsic characteristics of real-world energy consumption patterns [10]. The Holt-Winters exponential smoothing technique demonstrates proficiency in processing seasonal variations but exhibits constrained adaptability when confronting abrupt structural modifications in consumption behavior [11]. Foundational investigations into cyclostationary signal processing have established robust mathematical frameworks for examining phenomena characterized by periodically fluctuating statistical characteristics a fundamental attribute observed across numerous engineering systems, particularly within electrical grid infrastructures.

Scholarly investigations focusing on coherence-based covariance assessment of periodically correlated random processes (PCRP) have validated the computational efficacy of PCRP methodologies for signal analysis exhibiting periodic structural characteristics [12]. Subsequent methodological advancements addressing processes with indeterminate nonstationarity intervals have significantly broadened the scope of practical implementations [13]. Least-squares-based fundamental frequency identification techniques for periodically nonstationary stochastic signals have exhibited remarkable precision in characterizing periodic signal attributes [14]. Mathematical representation of cyclical phenomena through cyclically correlated stochastic processes has provided theoretical underpinnings for analyzing sophisticated technical infrastructures [15]. The successful implementation of PCRP frameworks for modeling diurnal computer network traffic patterns has confirmed the methodological versatility [16], while application to organizational electrical consumption modeling has demonstrated practical effectiveness within authentic energy systems [17].

Machine learning paradigms deliver exceptional predictive performance yet frequently function as opaque computational architectures, providing minimal insight into underlying physical mechanisms governing energy processes [18]. Recent studies have demonstrated neural network applications for electricity consumption forecasting in specialized sectors such as aviation enterprises, where reconfiguration of power supply systems requires adaptive prediction models [19]. Deep learning frameworks excel in capturing nonlinear interdependencies within energy datasets, but present significant limitations regarding interpretability of computational outcomes [20]. While machine learning approaches have shown effectiveness across various domains, including medical applications [21], contemporary intelligent systems for energy distribution utilizing artificial intelligence technologies illustrate substantial potential for integrating PCRP methodologies with advanced machine learning frameworks [22].

Current research developments indicate remarkable advancement in electrical consumption forecasting capabilities. Linear filtering techniques for statistical examination of periodically correlated stochastic processes establish foundational principles for precise prediction methodologies [23], while AI-enabled energy distribution systems demonstrate computational effectiveness within intelligent building infrastructures [24]. Novel modeling approaches for diurnal electricity consumption patterns substantially exceed the performance of traditional methodologies, ensuring reliable forecasting across extensive datasets [25].

The implementation of PCRP frameworks for electrical consumption modeling through statistical averaging procedures to enhance estimation reliability remains underexplored, thereby establishing the scientific rationale for developing specialized methodologies tailored to energy sector applications.

Proposed method

An adequate model for the electricity consumption signal as stochastic oscillations with repeatability is the PCRP (Periodically Correlated Random Process). Such a model, in its most generalized form, integrates random fluctuations of signal values with their repetitive structure, considering it as periodicity of probabilistic characteristics according to the expression:

$$\xi(t) = \sum_{k\epsilon Z} \xi_k(t) e^{i\frac{2\pi k}{T}t}, t \epsilon \mathbf{R}, k \epsilon \mathbf{Z}, \quad (1)$$

where $\xi_k(t)$ – the stochastic component of the electricity consumption signal structure, represented as stationary-correlated processes (stationary components).

$e^{i\frac{2\pi k}{T}t}$ – the periodic (cyclic) component of the electricity consumption signal, with a daily period parameter T = 24 hours;

k – the stationary component number.

The representation of the electricity consumption signal through PCRP representation (1) provides justification for applying the component analysis method to its evaluation by assessing probabilistic characteristics as informative features for electricity consumption forecasting, which are indicators of variations in power system operation.

The component analysis method for electricity consumption signals is based on the assumption of periodicity of its characteristics over time, which enables their description in the form of Fourier series expansion:

$$\hat{b}_\xi(t,u) = \sum_{k\epsilon Z} \hat{B}_k(u) \exp(ik\frac{2\pi}{T}t), \quad (2)$$

The coefficients $\hat{B}_k(u)$ of the expansion estimates (2), which are the components of characteristics, are calculated according to the expressions:

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

The application of the component method to the analysis of electrical energy signals as PCRP models ensures the computation of estimates $\hat{B}_k(u)$, based on which it is possible to optimally describe the properties of energy systems taking into account both regular deterministic component laws and random component disturbances and perturbations to ensure effective forecasting of future loads and optimization of energy resource distribution.

To improve the statistical reliability of estimates $\hat{B}_k(u)$ and identification of stable patterns, an averaging procedure over components and time shifts was applied according to the expressions:

- *averaging over time shift:*

$$M_u\{\hat{B}_k(u)\} = \frac{1}{U_{max}}\sum_{u=1}^{U_{max}} \hat{B}_k(u), u = \overline{1, U_{max}}, k = \overline{1, K_{max}} \quad (4)$$

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

where k – the number of the correlation component of the electricity consumption signal;

u – the shift of the electricity consumption signal;

U_{max} – the maximum length of the time shift of the electricity consumption signal;

K_{max} – the maximum number of components of the electricity consumption signal.

For the electricity consumption signal as a PCRP, the component method provides significant improvement in the statistical reliability of estimates through the application of coherent averaging procedures. The mathematical properties of such procedures guarantee unbiasedness of estimates, consistency, and efficiency in the form of minimal variance among the class of unbiased estimates.

Results

The empirical validation and performance assessment of the PCRP framework employed a comprehensive electricity consumption dataset derived from residential infrastructure. The experimental dataset was organized according to a three-tier hierarchical architecture encompassing diurnal, hebdomadal, and monthly temporal scales, facilitating systematic analysis through PCRP component decomposition methodologies. Figure 3 illustrates the residential electrical consumption patterns observed during the interval from July 15 to August 15, 2025.

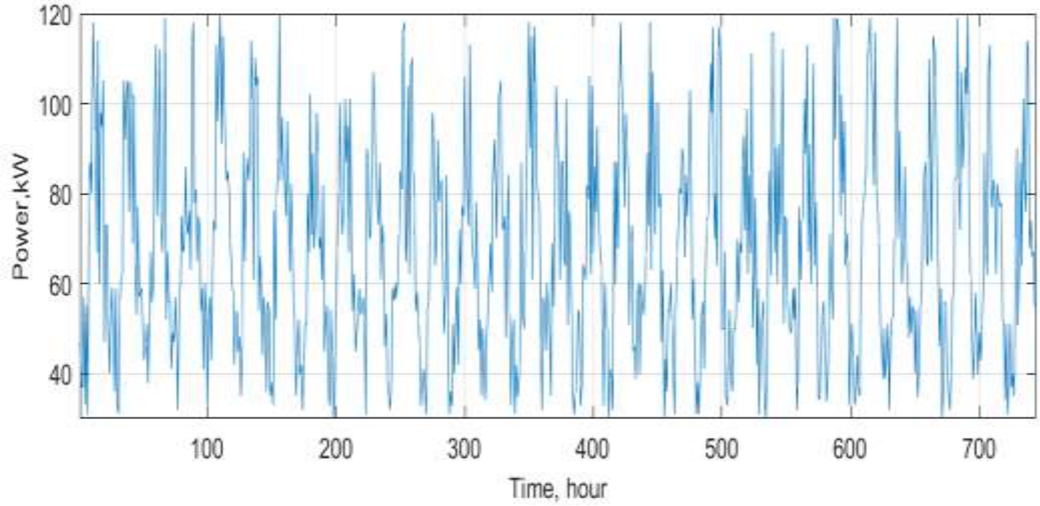

Fig. 3. Residential electricity consumption profile spanning July 15, 2025 to August 15, 2025

The monthly electrical consumption realization exhibits pronounced repetitive characteristics accompanied by substantial amplitude fluctuations across the monitoring duration. Systematic periodicity manifesting through consistent diurnal energy cycle reproduction was identified, substantiating the theoretical premise regarding daily component predominance within the aggregate load architecture and validating PCRP model implementation.

Weekly residential electricity consumption dynamics (Figure 4) demonstrate cyclical behavior characterized by diurnal amplitude modulations. Throughout the seven-day observation window, a consistent temporal rhythm emerges, wherein daytime consumption peaks alternate systematically with nocturnal minima. The diurnal components exhibit variable intensities contingent upon their positioning within the weekly cycle, necessitating multi-scale analytical approaches for comprehensive energy load characterization.

The absence of significant degradation during weekend intervals indicates continuity of fundamental energy processes. Consistent diurnal periodicity exhibiting minimal deviations between operational and non-operational days, combined with systematic day-night cycle reproduction, generates highly predictable energy consumption patterns, establishing the investigated system as optimal for PCRP methodology application.

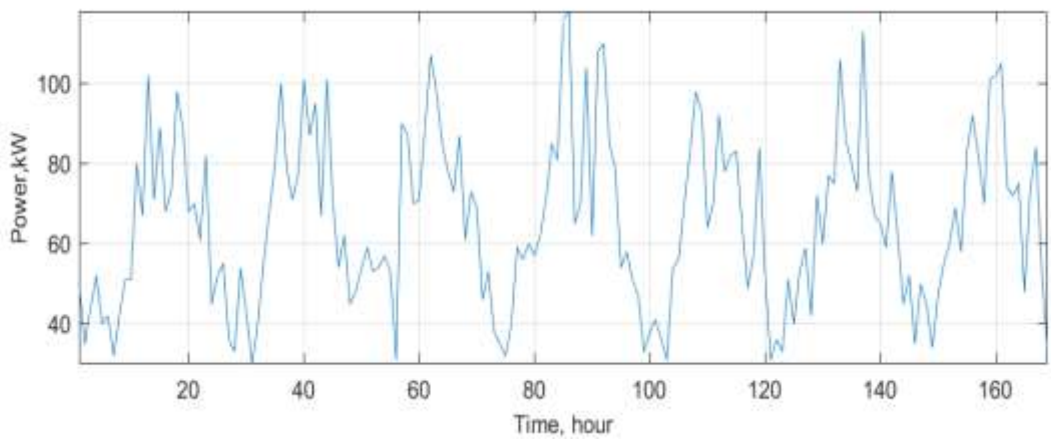

Fig. 4. Hebdomadal electricity consumption profile for residential infrastructure spanning July 21, 2025 to July 27, 2025

Comprehensive analysis of diurnal electricity consumption architecture involved identification of characteristic daily cycles demonstrating specific intra-diurnal patterns. The residential electrical consumption profiles for July 27, 2025 and August 2, 2025 encompass complete diurnal cycles while exhibiting characteristic amplitude variability. The identified patterns confirm systematic periodicity, with consistent peak reproduction occurring at 24-hour intervals.

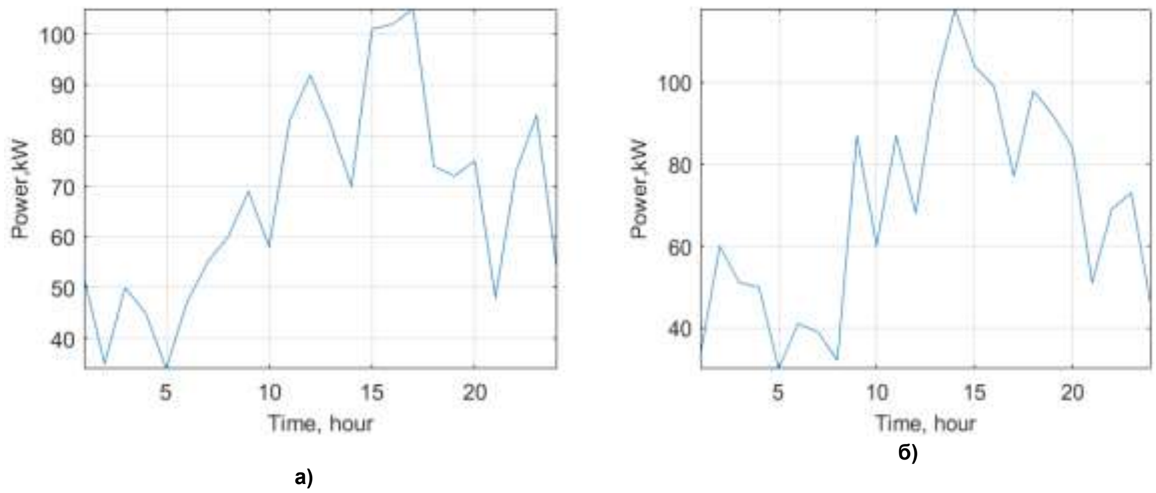

Fig. 5. Diurnal electricity consumption profiles for residential infrastructure: a) July 27, 2025; b) for August 2, 2025

Comprehensive analysis of experimental data across three temporal resolution levels monthly, weekly, and daily validates the presence of well-defined periodic structures within electricity consumption patterns. The characterized features indicate multi-hierarchical architecture of energy processes, wherein diurnal components establish fundamental structural frameworks, weekly variations reflect socio-economic determinants, and monthly dynamics demonstrate cyclical pattern stability. Such multi-scale periodicity establishes the investigated energy series as an optimal candidate for PCRP analytical methodologies, capable of effectively modeling both deterministic components and stochastic elements within energy load profiles.

Characterization of the mathematical framework for electricity consumption modeling required comprehensive analysis of real signal parameters. Investigation of consumption realizations within stationary model contexts revealed temporal transformation of probability density functions, indicating non-stationary characteristics of electrical consumption processes.

Figure 6 demonstrates PCRP component methodology implementation, specifically presenting computed values for component averaging $\bar{B}(t)$ (Figure 4a) and temporal averaging $\tilde{B}_k$ (Figure 4b) derived from residential electricity consumption signals.

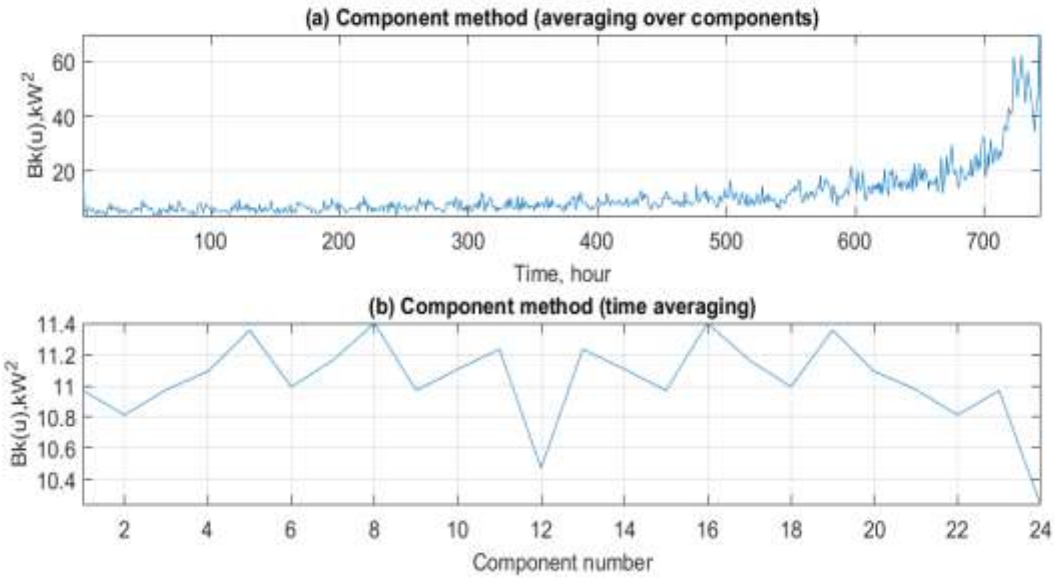

Fig. 6. Results of component method averaging: a) component averaging $\bar{B}(t)$; b) time averaging $\tilde{B}_k$

The revealed dynamics substantiate hypotheses regarding multi-scale non-stationarity within energy processes. The pronounced contrast between stability and activity periods indicates adaptive characteristics of electrical consumption systems, responding to external perturbations through differential operational modes. The observed behavior typifies energy systems incorporating renewable source integration, where low-variability periods alternate with intensive fluctuation episodes.

Figure 7 presents three-dimensional visualization of component method application results for residential electrical load analysis. The graphical representation demonstrates component variance dependence on component number and temporal variables. The vertical axis represents variance magnitudes. Analysis of the three-dimensional model reveals several fundamental patterns. Initially, significant variance increases are observed for primary components, achieving maximum values during initial observation periods. Subsequently, pronounced irregularity in energy distribution between components indicates low-frequency harmonic dominance within electrical load structures. Finally, temporal evolution demonstrates gradual oscillation intensity reduction, particularly evident for high-frequency components.

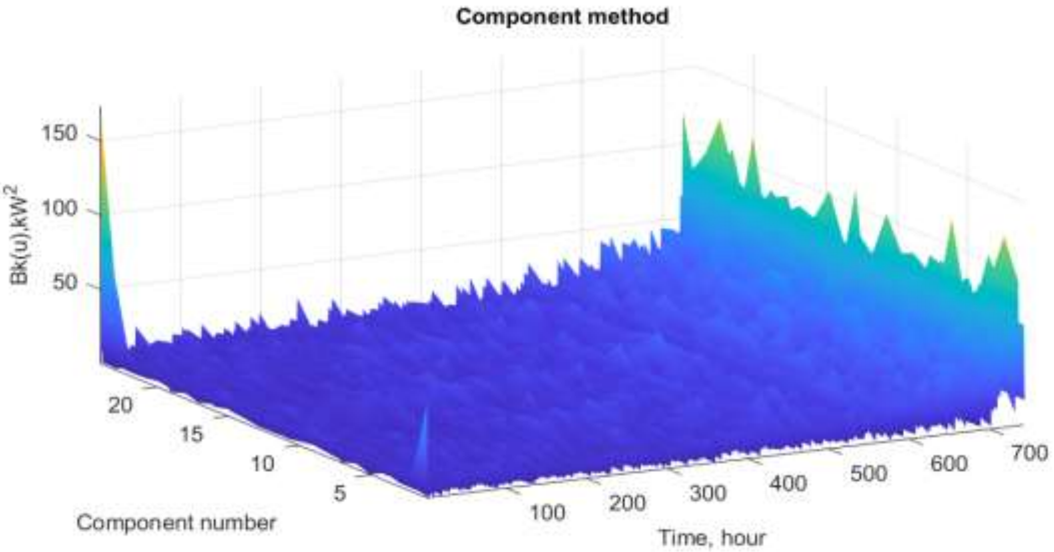

Fig. 7. Three-dimensional representation of the component method

The three-dimensional visualization exposes complex interaction dynamics between different frequency components of electrical load signals, phenomena undetectable through conventional analytical approaches. This provides enhanced understanding of physical processes within energy systems.

The graphical representation reflects temporal averaging results for individual components, illustrating energy distribution within frequency domains. Characteristic spectral distribution is observed with maxima for low-frequency components, gradual reduction to minimal values for medium-frequency components, and subsequent growth for high-frequency components. Such spectral configurations typify systems wherein fundamental harmonics (diurnal periodicity) predominate alongside high-frequency components reflecting short-term load fluctuations.

Discussion

The obtained results validate PCRP approach effectiveness for energy load analysis. The proposed mathematical framework demonstrates excellent correspondence with actual electricity consumption processes, surpassing traditional stationary method performance.

The revealed multi-scale electricity consumption structure aligns with previous research findings, confirming universal periodic properties of energy systems regardless of scale and consumer categories. Daily component dominance within spectral distribution corresponds to general patterns of residential energy system functionality.

Averaging procedures provide substantial variance reduction in statistical estimates compared to conventional methods and facilitate stable pattern identification, critically important for energy resource forecasting and planning. This enables development of more reliable predictive models with enhanced accuracy.

Physical interpretability of results represents a key advantage compared to machine learning methodologies. Each identified component possesses clear physical interpretation, enabling energy specialists to comprehend process characteristics and make informed decisions regarding energy system management.

Correlation analysis of electricity consumption established that correlation functions as ensemble realizations demonstrate periodic properties, indicating signal cyclicity and structured characteristics.

Electricity consumption structure analysis demonstrates that individual diurnal realizations are characterized by both random load fluctuations caused by unpredictable factors and regular diurnal patterns reflecting stable electricity consumption rhythms. Electricity consumption belongs to finite process classifications, as individual diurnal realizations possess clearly defined boundaries with repeatable structures. A fundamental process feature is the presence of correlational relationships between different diurnal realizations, conditioned by energy system inertia, consumer behavioral patterns, and residential infrastructure functionality.

Conclusions

The experimental findings substantiate the computational efficacy of PCRP methodologies for energy load characterization. The developed mathematical framework exhibits exceptional concordance with authentic electricity consumption dynamics while significantly exceeding the analytical capabilities of conventional stationary approaches. The identified multi-hierarchical electricity consumption architecture aligns with established research outcomes, validating the universal characteristics of periodic phenomena within energy infrastructures irrespective of operational scale or consumer demographics. The observed diurnal component predominance within spectral distributions reflects fundamental patterns inherent to residential energy system operations.

Energy consumption processes exhibit substantial temporal variability attributed to meteorological influences, economic fluctuations, and technological evolution. The proposed methodology inherently accommodates such variations through multiple adaptive mechanisms: dynamic basis recalibration utilizing sliding window computations to monitor system evolution across temporal domains; hierarchical decomposition frameworks enabling multi-scale processing at appropriate resolution levels for effective modeling of both transient fluctuations and secular trends; and automated component optimization through information-theoretic criteria for determining optimal component quantities across individual temporal intervals.

Despite demonstrated advantages, the methodology presents specific operational constraints. Data acquisition requirements necessitate sufficiently extensive observation sequences for reliable periodic component estimation. Computational complexity scales proportionally with component quantity and temporal series duration. Sensitivity to anomalous observations indicates that outlier values may influence parameter estimation accuracy, although robust analytical variants provide mechanisms for mitigating such effects.

The research outcomes present extensive practical deployment opportunities across multiple domains. Enhanced load prediction capabilities deliver improved accuracy for short-term and intermediate-term forecasting applications. Electrical resource optimization facilitates strategic generating capacity distribution planning. Intelligent grid management systems enable adaptive demand response control mechanisms. Renewable energy integration frameworks provide enhanced forecasting and management capabilities for sustainable energy sources.

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