Component method for analyzing the energy consumption signal as a periodically correlated random process*

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Abstract

The article focuses on the development and application of a component analysis method for power consumption signals within the mathematical framework of Periodically Correlated Random Processes (PCRP). Using experimental data from a private household over a one-month period, the temporal and frequency structure of the load with a pronounced daily periodicity was analyzed. The proposed method ensures physical interpretability of results and high statistical reliability through the use of coherent averaging procedures over time shifts and components. Three-dimensional visualization of spectral evolution revealed complex dynamic interactions between frequency components of the energy signal, which cannot be detected using traditional analysis methods. The results confirm the effectiveness of component analysis for identifying stable consumption patterns, forecasting electrical loads, and optimizing energy supply processes. The proposed approach can be applied to energy planning, smart grid management, and the development of adaptive forecasting models.

Keywords

electricity consumption, mathematical modeling, periodically correlated random processes, component method, load forecasting

1. Introduction

With the advancement of energy systems, these systems are becoming increasingly complex and branched. Moreover, rapid technological transformations including widespread digitalization renewable energy integration and smart grid deployments have fundamentally altered electricity consumption patterns creating new analytical challenges for traditional forecasting methods. This creates a need for new tools for modeling and forecasting electricity consumption.

Classical analysis methods no longer provide adequate representation of stochastic fluctuations and dynamic changes in loads [1]. A characteristic feature of modern energy loads is the presence of periodic patterns, particularly daily, weekly, and seasonal cycles, combined with random fluctuations [2].

The latter are driven by consumer behavioral factors and the instability of renewable energy generation. This necessitates the application of approaches that organically combine deterministic and stochastic analysis. Energy loads have acquired a fundamentally new character, manifested in the combination of dynamicity, nonlinearity, and multifactorial nature [3].

*ITTAP'2025: 5th International Workshop on Information Technologies: Theoretical and Applied Problems, October 22-24, 2025, Ternopil, Ukraine, Opole, Poland

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Reliable electricity consumption forecasting is fundamental to energy system operations affecting everything from daily grid dispatch decisions to long-term infrastructure investments, making the development of robust analytical methods an important priority for the energy sector.

The proposed approach involves decomposing the total load into structural components: the trend as a long-term tendency of changes, periodic components in the form of cyclical oscillations of various scales, and a noise component representing random deviations [4]. The application of component analysis methods for electricity consumption based on representing energy loads as periodically correlated random processes enables the identification of hidden patterns and the creation of adaptive predictive models with enhanced accuracy [5, 6]. The development of IoT technologies and data processing systems in smart cities creates additional opportunities for effective data presentation, identification of stable consumption patterns, and improvement of energy planning accuracy [7].

Its implementation will enable efficient data representations, identification of stable consumption patterns, and improved accuracy in energy planning [8].

2. Related Work

Contemporary approaches to energy system analysis can be classified into three main categories: traditional statistical methods, machine learning methods, and hybrid approaches, each having its advantages and limitations in modeling complex energy processes.

Traditional statistical methods are based on the assumption of time series stationarity [9]. ARIMA models, applied for short-term load forecasting, assume stationarity after differencing, which does not always correspond to the real properties of energy processes [10]. Holt-Winters exponential smoothing is effective for seasonal data, but has limited ability to adapt to structural changes in consumption [11]. Fundamental research on cyclostationary processes has laid the mathematical foundation for analyzing signals with periodically varying statistical properties, which is a natural characteristic of many technical systems, including energy networks.

Research on coherent covariance analysis of periodically correlated random processes has demonstrated the effectiveness of the PCRP approach for analyzing signals with periodic structure [12], while its further development for processes with unknown nonstationarity periods has expanded application possibilities [13]. Methods for fundamental frequency estimation of periodically nonstationary random signals using least squares have demonstrated high accuracy in identifying periodic characteristics [14]. Mathematical modeling of cyclic signals as cyclically correlated random processes has established theoretical foundations for analyzing complex technical systems [15], while the application of PCRP models for modeling daily computer network traffic confirmed the universality of the approach [16], and modeling of organizational electricity consumption processes proved the effectiveness of the Periodically Correlated Random Processes approach for real energy systems [17].

Machine learning methods provide high forecasting accuracy but often operate as "black boxes," not providing understanding of the physical nature of processes [18]. Deep learning is effective for modeling nonlinear dependencies in energy data but is limited in result interpretation [19]. Modern computer systems for energy distribution using artificial intelligence demonstrate the potential for integrating PCRP methods with machine learning technologies [20].

Recent research shows significant progress in electricity consumption forecasting. Linear filtering methods for statistical analysis of periodically correlated random processes provide a foundation for accurate forecasting [21], while computer systems for energy distribution using artificial intelligence demonstrate the effectiveness of intelligent methods for smart buildings [22]. New methods for modeling daily electricity consumption significantly outperform classical approaches, ensuring accurate forecasting of large data volumes [23].

The application of PCRP models for electricity consumption using averaging procedures to improve statistical reliability of estimates remains insufficiently investigated, which justifies the relevance of developing specialized methods for energy applications.

3. Methodology

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:

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

where $\xi(t)$- 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 implementation of PCRP methodology requires careful consideration of data quality parameters. Signal preprocessing includes outlier detection using statistical thresholds and gap-filling procedures for missing measurements to ensure reliable component estimation. The method's effectiveness depends on maintaining temporal continuity in the observation series.

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:

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

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

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

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:

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

- averaging over component:

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

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.

4. Results and Discussion

To conduct the study and verify the performance of the PCRP model, a time series of electricity consumption signal from a private household was formed. The experimental data were structured into a three-level hierarchical system daily, weekly, and monthly scales which enables analysis using the PCRP component method.

Figure 1 presents the electricity consumption of a private household for the period from April 15 to May 15, 2025.

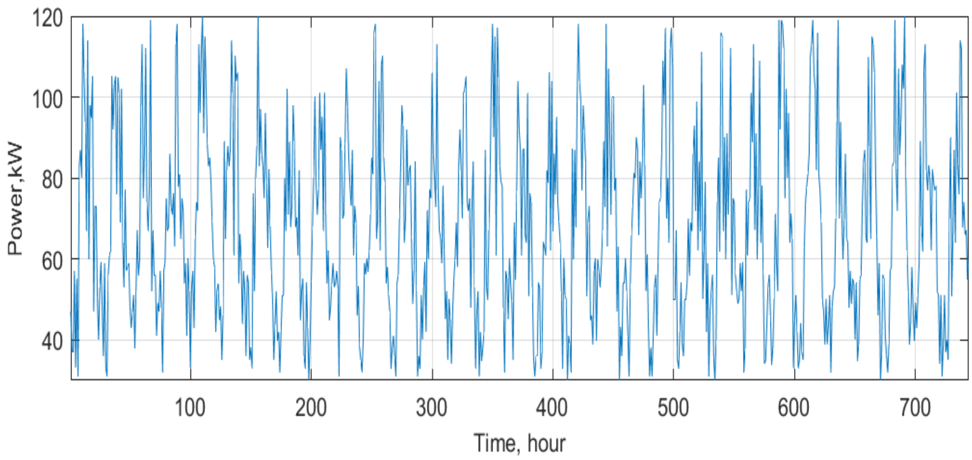


Figure 1: Electricity consumption of a private household from April 15, 2025 to May 15, 2025.

The monthly realization of private household electricity consumption is characterized by a distinct repetitive structure with significant amplitude variations throughout the observation period. Periodicity with regular reproduction of energy cycles every day was identified, which confirms the hypothesis about the dominance of the daily component in the overall load structure and justifies the application of the PCRP model.

The weekly electricity consumption of the private household (Figure 2) reveals cyclic behavior with daily amplitude variations. Throughout the seven-day period, a stable rhythm is formed where daytime maxima alternate with nighttime minima. The daily components demonstrate variable intensity depending on their position in the weekly cycle, which initiated the need for multi-scale analysis of energy load.

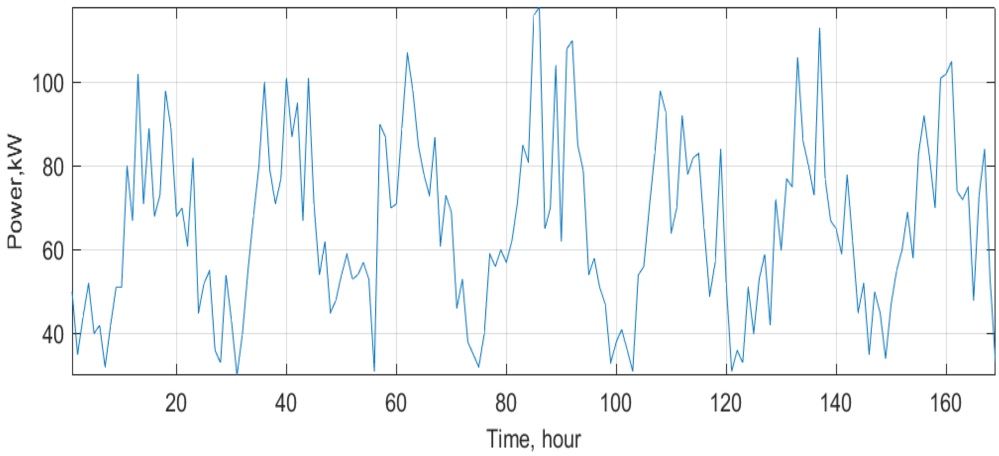
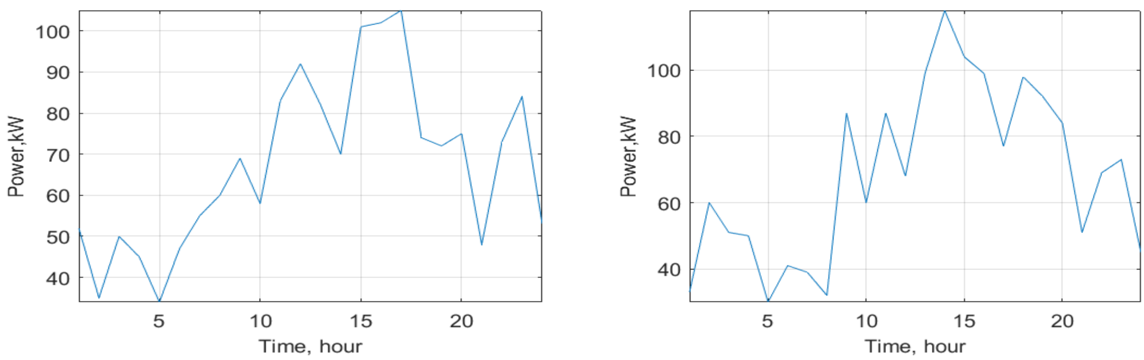


Figure 2: Weekly electricity consumption schedule of a private household from April 21, 2025 to April 27, 2025.

The absence of critical degradation during weekend periods indicates the continuity of basic energy processes. Constant daily periodicity with minimal deviations between working and non-working days, and regular reproduction of day-night cycles form highly predictable energy patterns, making the studied system optimal for applying the PCRP approach.

For in-depth analysis of the daily electricity consumption structure, a characteristic daily cycle was identified, which demonstrates specific intra-daily patterns. The daily electricity consumption of the private household for April 27, 2025 and May 2, 2025 covers a complete daily cycle and demonstrates characteristic amplitude variability. The identified pattern confirms stable periodicity with systematic reproduction of peaks every 24 hours.



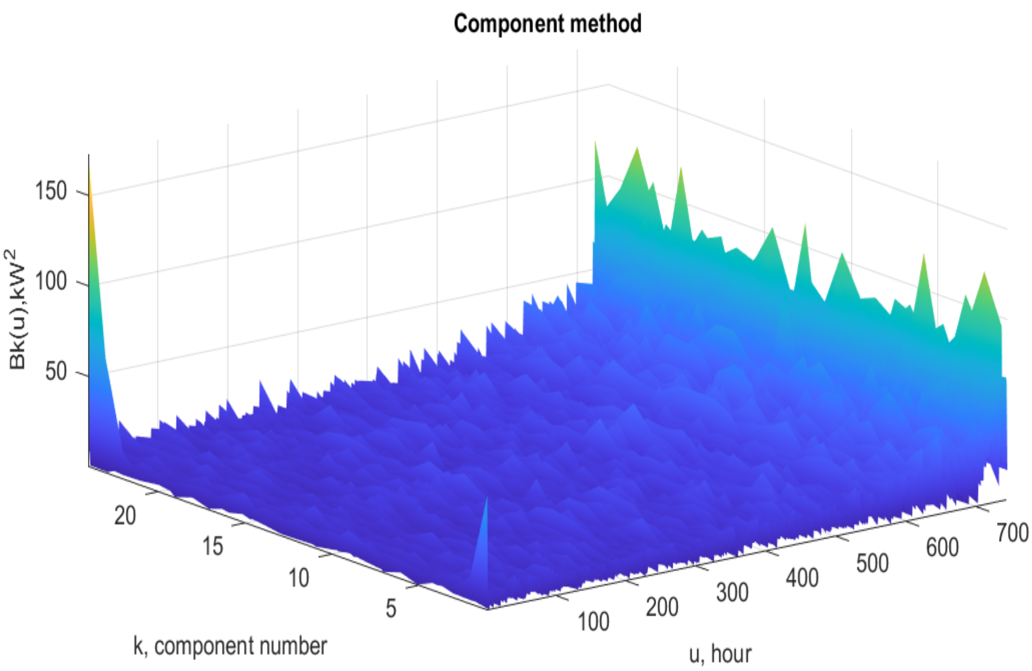
a) b)

Figure 3: Daily electricity consumption schedule of a private household: a) for April 27, 2025 b) for May 2, 2025

Integral analysis of experimental data at three levels of detail monthly, weekly, and daily confirms the presence of clearly structured periodicities in electricity consumption. The identified characteristics indicate a multi-level hierarchical structure of the energy process, where daily components form the basic architecture reflecting physiological and technological cycles, weekly variations reflect socio-economic determinants including work schedules, and monthly dynamics demonstrate seasonal stability. This hierarchical organization exhibits interdependencies where higher-frequency components modulate lower-frequency ones creating complex interaction patterns. Such multi-level periodicity makes the studied energy series an ideal object for applying the PCRP analysis method, capable of effectively modeling both deterministic components and stochastic elements of energy load.

To determine the architecture of the mathematical model of electricity consumption, the parameters of the real signal were analyzed through statistical testing. When studying the consumption realization in the context of a stationary model, it was found that probability density functions transform systematically in temporal space exhibiting time-dependent statistical properties, which indicates the non-stationary nature of the electricity consumption process.

Figure 4 presents a 3D visualization of the results of applying the component method to the analysis of the energy consumption signal of a private household. The graph displays the dependence of the variance of correlation components on their number and observation time revealing the temporal evolution of spectral characteristics. The vertical axis corresponds to variance values while the horizontal axes represent the time course and component number enabling comprehensive analysis of both temporal and spectral properties simultaneously.



Analysis of the obtained model reveals several characteristic patterns in the energy consumption signal structure.

At the initial stage of observations, a sharp increase in the variance of the first components is observed indicating the dominance of low-frequency components in the signal structure. The energy distribution among components demonstrates uneven characteristics pointing to a heterogeneous frequency structure of energy consumption with distinct spectral properties.

Furthermore, in the temporal dynamics a gradual decrease in oscillation intensity becomes noticeable particularly for high-frequency harmonics suggesting the prevalence of stable long-term consumption trends over short-term fluctuations. The computational complexity of the component analysis scales linearly with observation length making the method suitable for periodic analysis updates in smart grid applications.

Through such 3D visualization, it is possible to analyze more deeply the interaction between temporal and frequency characteristics of the energy consumption signal, which is inaccessible when using classical one-dimensional methods. This approach enables the identification of stable frequency structures and detection of potential changes in energy system operating modes.

The hierarchical structure of periodic components demonstrates the method's capability to distinguish between operational patterns and behavioral patterns enabling targeted optimization strategies for different temporal scales in energy management systems.

Figure 5 shows the averaging of the 3D correlation components of the private household electricity consumption signal as a PCRP (Fig. 4) by components (Fig. 5a) and time shifts (Fig. 5b).

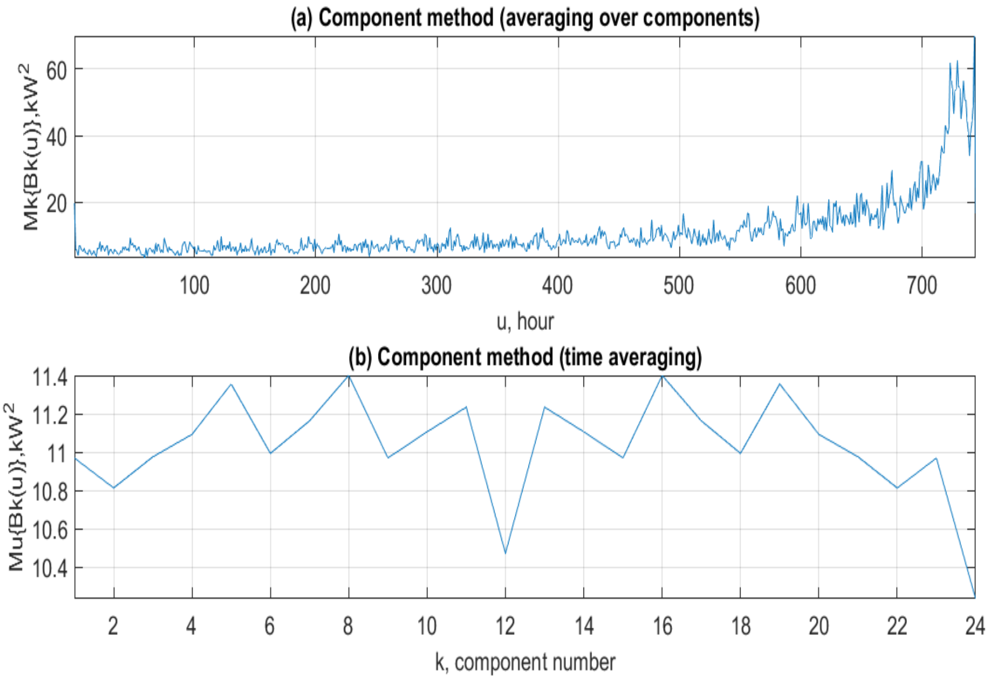


Figure 5: Implementations of the averaging of correlation components:
a) averaging by components; b) averaging by time shifts

The obtained results of component analysis of energy consumption (Fig. 5) indicate the presence of stable patterns in the temporal and frequency structures of the signal.

According to the graph (Fig. 5a), component averaging showed that throughout most of the observation period, the energy consumption level remains stable, characterizing the system as relatively stationary. However, at the end of the interval, a sharp increase in average energy power was recorded, which may indicate the emergence of peak load or a change in the operating mode of the energy system.

Analysis of the graph (Fig. 5b), constructed based on time averaging results, revealed an uneven distribution of energy contribution among individual correlation components. The presence of local maxima for certain component numbers (specifically, 5–6 and 17–18) indicates the dominance of individual frequency components in the energy consumption signal, which may be caused by periodic technological or daily cycles. Minimum values for individual components (for example, the 12th and 24th) indicate a weak influence of these frequencies on the overall energy balance.

Thus, the performed component analysis allowed identifying both temporal features of energy consumption changes and the structure of its frequency components. This confirms the feasibility of applying the correlation component method for assessing stability and identifying periodic trends in energy consumption processes, which can be used for load forecasting and optimization of energy systems.

5. Conclusion

The study presents a component analysis method for energy consumption signals based on periodically correlated random processes (PCRP) model. Analysis of experimental data from a private household demonstrated the effectiveness of this methodology for detecting hidden temporal and frequency patterns in energy consumption structure.

The research established the presence of clearly expressed daily periodicity in the energy consumption signal confirming the feasibility of using PCRP for modeling real energy processes. The component method was demonstrated to provide enhanced statistical reliability of estimates through the application of coherent averaging procedures across time shifts and components.

3D visualization of spectral evolution revealed complex dynamics of interaction between frequency components of the signal which cannot be detected by traditional analysis methods. Additionally multi-level periodicity including daily weekly and monthly patterns was shown to form a hierarchical load structure suitable for building adaptive forecasting models.

The obtained results confirm that the application of component analysis within PCRP framework is a promising approach for optimizing energy planning systems load forecasting and smart grid management while acknowledging the method's data requirements for reliable implementation.

Further research can be directed toward integrating the component method with machine learning algorithms to improve the accuracy of long-term forecasts, develop intelligent energy process management systems, and address computational challenges associated with shorter observation periods in real-time applications.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to grammar and spell check, and improve the text readability. After using the tool, the authors reviewed and edited the content as needed to take full responsibility for the publication’s content.

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