The 55th International October Conference on Mining and Metallurgy
15 - 17 October 2024, Kladovo, Serbia
https://ioc.irmbor.co.rs

DOI: 10.5937/IOC24441K Original Scientific Paper-Electronics

COMPARATIVE ANALYSIS OF THE TIME SERIES DECOMPOSITION TECHNIQUES IN THE ENERGY SECTOR APPLICATIONS

Marijana Pavlov-Kagadejev[1a], Aleksandra Milosavljevic[1b], Milan Radivojevic[1c]

[1]Mining and Metallurgy Institute Bor, Alberta Ajnštajna 1, 19210 Bor, Serbia

[1a] marijana.pavlov@irmbor.co.rs, https://orcid.org/0000-0003-1090-6351;
[1b] aleksandra.milosavljevic@irmbor.co.rs, https://orcid.org/0000-0003-3841-7357;
[1c] milan.radivojevic@irmbor.co.rs, https://orcid.org/0000-0003-2337-0306

Abstract

Time series decomposition is significant for understanding the consumption, production, and pricing in the energy sector analysis. This paper presents the comparative analyses of three important decomposition techniques: the Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), and Seasonal-Trend decomposition using the Loess (STL). The methodology, advantages, limitations, and applications of these techniques are described to help users selecting the most appropriate method.

Keywords*: time series, decomposition, EMD, VMD, STL*

1. INTRODUCTION

The time series data analysis is essential for effectively managing consumption, production, and price forecasting in the energy sector. By applying this technique, the complex datasets can be separated into simpler components, enhancing the analysis and modeling of those data [1]. *The time series decomposition techniques are important tools for isolating and examining various aspects of data, such as trends, seasonal variations, and residual components. After applying these techniques, it is easier to uncover the periodic fluctuations, long-term trends, and irregular elements which are critical for accurate forecasting in the energy industry [2].*

2. DECOMPOSITION TECHNIQUES

Among the various decomposition methods available, three notable techniques are the Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), and Seasonal-Trend decomposition using the Loess (STL). Each method has its unique approach and strengths. This paper compares three prominent decomposition techniques: the EMD, VMD and STL.

2.1 Empirical Mode Decomposition (EMD)

The EMD decomposes a complex time series data into the Intrinsic Mode Functions (IMFs) and residual component. This process involves extracting the finite number of IMFs through identifying the local extrema, constructing envelopes, and subtracting them from the original signal. The EMD is effective for noise reduction in the non-stationary time series and particularly useful in the wind speed data analysis [3-5]. Steps of EMD process [6]:

- Determine the local maximum and minimum value for any processed signal $x(t)$ and record $h_1(t)$

$$h_1 = x(t) - m_1(t) \tag{1}$$

where $m_1(t)$ is the mean of the upper and lower envelopes.

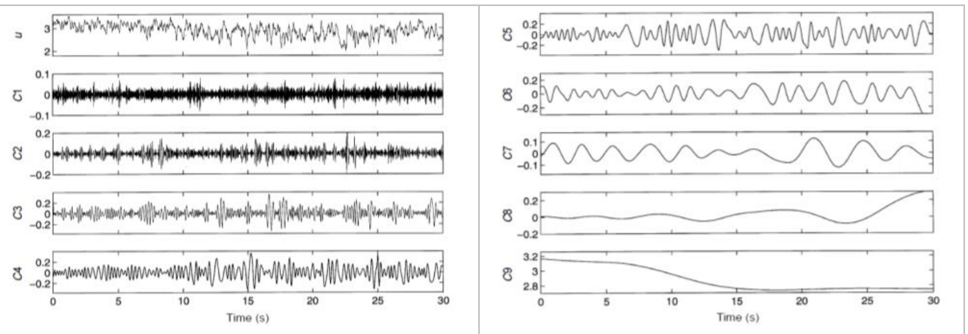
- Difference signal $r_1(t)$ is obtained by separating $h_1(t)$ from $x(t)$:

$$\begin{aligned} r_1(t) &= x(t) - h_1(t) \\ r_2(t) &= r_1(t) - h_2(t) \\ &\vdots \\ r_n(t) &= r_{n-1}(t) - h_n(t) \end{aligned} \tag{2}$$

The signal $x(t)$ can be represented as a sum of n IMFs and residual signal shown in Equation (3):

$$x(t) = \sum_{j=1}^{n} h_j(t) + r_n(t) \tag{3}$$

where $r_n(t)$ is the residual, $h_j(t)$ is the j-th IMF, $j = 1, 2\ldots, n$, represents the different components of the signal from high to low frequencies, respectively. Figure 1 represents an example of the resulting EMD components from a wind data.



a) b)

Figure 1. *The resulting EMD components from a wind data: a) original data and components c1- c4; b) components c5 - c9, where c9 component, represents trend, not an IMF [3]*

2.2 Variational Mode Decomposition (VMD)

The Variational Mode Decomposition (VMD) is based on the Wiener filtering and Hilbert transform and represents the non-recursive signal processing technology. The original input signal $f(t)$ can be decomposed into a series of discrete sub-signals $u_k(t)$, which bandwidth is limited around the center frequency ω_k (Equation (4)) [7-10].

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \quad , \quad s.t.\sum_{k=1}^{K}u_k=f(t) \tag{4}$$

where K is the number of decomposed modes, $\{u_k\} = \{u_1,u_2\cdots u_K\}$ are decomposed modal components with the center frequencies $\{\omega_k\} = \{\omega_1,\omega_2\cdots\omega_K\}$, ∂_t is partial derivative. $\delta(t)$ represents the Dirac distribution, $f(t)$ is the original input signal, $u_k(t)$ represents k-th subsequence of $f(t)$, * a convolution operator.
The Lagrange multiplication operator λ and the quadratic penalty factor α are introduced in order to obtain the optimal solution of constrained variational mode, as it is shown in equation [4]:

$$L(\{u_k\},\{\omega_k\},\lambda)=\alpha\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2=\left\|f(t)-\sum_{k=1}^{K}u_k(t)\right\|_2^2+\left\langle\lambda_t,f(t)-\sum_{k=1}^{K}u_k(t)\right\rangle \tag{5}$$

Iteration stop condition is:

$$\frac{\sum_{k=1}^{K}\left\|\hat{u}_k^{n+1}(\omega)-\hat{u}_k^{n}(\omega)\right\|_2^2}{\left\|\hat{u}_k^{n}(\omega)\right\|_2^2}<\xi \tag{6}$$

An example of the VMD technique for the wind speed data is shown in Figure 2 [11]. The original wind speed is decomposed into five components with different frequencies.

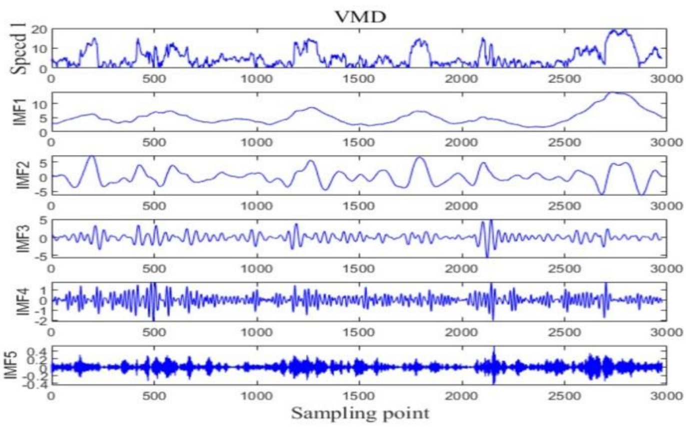


Figure 2. *Sample of the VMD technique wind speed data [11]*

2.3 Seasonal-Trend Decomposition using Loess (STL)

The STL decomposes a time series into seasonal, trend, and residual components using the local regression (loess). The method handles varying seasonal effects and adjusts to the changes in the seasonal patterns [12].

$$Y_t = T_t + S_t + R_t \quad (7)$$

where Y_t represents the original time series, T_t is a trend, S_t denotes a seasonal and R_t is a residual component. An example of the STL for electricity consumption data is shown in Figure 3[13].

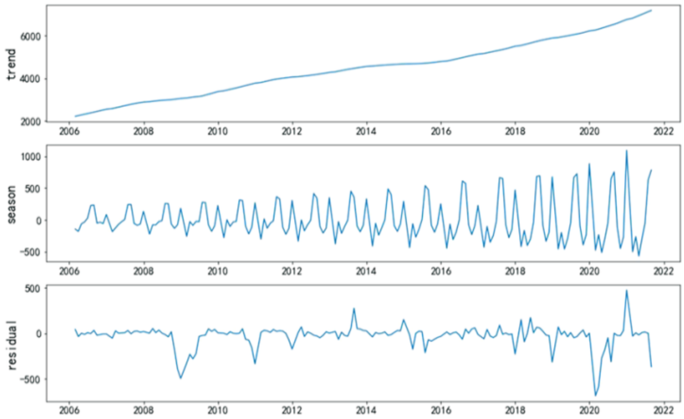


Figure 3. *Trend, seasonal, and residual for electricity consumption data decomposed by the STL [13]*

3. COMPARISON OF TECHNIQUES

Comparison of the EMD, VMD and STL decomposition techniques is represented in Table 1.

Table 1. *Comparison of decomposition techniques*

Technique	Flexibility	Computational Demand	Frequency Separation	Seasonal Handling	Interpretability	Key Disadvantages
EMD	High	High	Medium	Medium	Medium	Sensitive to noise; Complex interpretation
VMD	Medium	Very High	High	Low	Medium	Requires careful parameter tuning
STL	High	High	Low	High	High	Computationally intensive

As it is presented in Table 1, the advantages of EMD technique are its adaptivity and flexibility, but it is very sensitive to noise and iterative process can be computationally intensive. The VMD provides a clear frequency-based component separation and precision, but it requires the significant computational resources and optimal results depend on careful parameter tuning. The STL technique characteristic is flexibility in seasonality and it provides the clear and interpretable components. Disadvantages of the STL are a computational intensity (for large datasets), and requires a careful parameter tuning and implementation.

4. CONCLUSION

Choosing the appropriate decomposition technique for the time series analysis in the energy sector depends on the data characteristics and analysis goals. The EMD is useful for the nonlinear and non-stationary data, while the VMD offers a precise frequency-based separation. The STL is effective for handling the complex seasonal patterns. The future research may benefit from combining these methods to enhance accuracy and interpretability in the energy data analysis.

ACKNOWLEDGEMENTS

This work was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia. Contract on realization and financing of the scientific research work of the Mining and Metallurgy Institute Bor in 2024, Contract No.: 451-03-66/2024-03/ 200052.

REFERENCES

[1] Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M.: Time Series Analysis: Forecasting and Control. John Wiley & Sons, 2015.
[2] Hyndman, R. J.: Forecasting: Principles and Practice. OTexts, 2018.
[3] Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C., Liu, H.H.: The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-Stationary Time Series Analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 1998, 454(1971), pp.903-995
[4] Rehman, N., Mandic, D.P.: Multivariate Empirical Mode Decomposition. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2010, 466(2117), pp.1291-1302
[5] Wang, D., Cui, X., Niu, D.: Wind Power Forecasting Based on lstm Improved by Emd-Pca-Rf. Sustainability, 2022, 14(12), 7307
[6] Pavlov-Kagadejev, M., Jovanovic, L., Bacanin, N., Deveci, M., Zivkovic, M., Tuba, M., Strumberger, I., Pedrycz, W.: Optimizing Long-Short-Term Memory Models Via Metaheuristics for Decomposition Aided Wind Energy Generation Forecasting. Artificial Intelligence Review 57(3),2024, pgs. 45
[7] Dragomiretskiy, K., Zosso, D.: Variational Mode Decomposition. IEEE Transaction on Signal Processing, 2013, 62(3), pp. 531–544.
[8] Rehman, N., Aftab, H.: Multivariate Variational Mode Decomposition. IEEE Transactions on Signal Processing, 2019, 67(23), 6039–6052
[9] Zhang, T., Tang, Z., Wu, J., Du, X., Chen, K.: Multi-Step-Ahead Crude Oil Price Forecasting Based on Two-Layer Decomposition Technique and Extreme Learning Machine Optimized by the Particle Swarm Optimization Algorithm, Energy, 2021, 229,120797
[10] Wang, N., Li, Z.: Short Term Power Load Forecasting Based on Bes-Vmd and Cnn-Bi-Lstm Method with Error Correction. Frontiers in Energy Research,2023, 10

[11] Wang Q., Zhang L.: Short-Term Wind Speed Prediction of Wind Farm Based on TSO-VMD-BiLSTM. PeerJ Computer Science, 2024, 10, e2032

[12] Cleveland. R.B., Cleveland, W.S., McRae, J.E., Terpenning, I: STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics, 1990, 6(1), p.3-73.

[13] Zhang, X., Li, R.: A Novel Decomposition and Combination Technique for Forecasting Monthly Electricity Consumption. Frontiers in Energy Research, 2021, 9, 792358.