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# A Method for Augmentation of Multidimensional Time Series in Equipment Health Monitoring Tasks

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**Abstract**—The paper proposes a decomposing data augmentation method. As against the available ones, it handles multidimensional time series and during the augmentation retains the general trend and the structure of multidimensional data based on plant sensor readings. The gist of the method proposed is the application of multilevel variational mode decomposition coupled with conventional augmentation techniques. The method was verified using real-life multidimensional time series for thermocouples and load cells. The augmentation results were analyzed using MAE criterion as well as stochastic process PDF.

*Keywords*: equipment state diagnosis, sensor readings, augmentation, multidimensional data, synthetic data, variational mode decomposition

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## 1. INTRODUCTION

Data augmentation refers to the generation of new synthetic data that maintains similarity to the original dataset. Currently, the development of data augmentation techniques represents one of the most pressing challenges in measurement data preprocessing, with applications in several critical scenarios:

(1) When obtaining a sufficiently large dataset for developing adequate mathematical models is prohibitively expensive due to high experimental costs.

(2) When addressing missing data issues that frequently occur during practical implementation of predictive models in industrial settings, caused by system failures, production stoppages, or other disruptions.

(3) When generating anonymized sensor data is required for model testing and public dissemination of results.

Conventional data augmentation techniques employ various manipulations of original data to create synthetic samples, including: time series noise injection [1], scaling method, magnitude warping [2], time warping, window warping [3], rotation, and permutation [2] and several other methods [4]. These approaches share a fundamental characteristic: they operate by distorting, reducing, enlarging, or otherwise modifying the original dataset. This leads to a specific challenge in their application to sensor signal processing — the potential for excessive distortion relative to the original signal, which may adversely affect subsequent model development.

Furthermore, the aforementioned methods demonstrate a crucial limitation: they cannot effectively process sets of different signals that are synchronized in time. This represents a common scenario in industrial applications where simultaneous recording from multiple sensors is required for mathematical model development. Such signals typically exhibit shared temporal characteristics (outliers, trends, etc.), but applying independent augmentation to each signal disrupts these synchronized features, resulting in incorrect data for subsequent analysis.

Recent trends in data augmentation have shifted toward machine learning approaches, particularly:

- Generative adversarial networks (GANs) [5], which synthesize completely new datasets by learning the underlying data distribution from original samples
- Variational autoencoders (VAEs) [6], which generate data by mixing features from learned probability distributions rather than creating entirely novel samples

However, these advanced methods present two significant limitations:

(1) They demand substantial volumes of original training data, which are often unavailable in practical applications.

(2) The augmentation process requires considerable computational time, even for relatively small signals (e.g., 1000 data points), frequently necessitating segmented dataset processing that further complicates implementation.

We emphasize that this study does not address methods for generating stationary random processes with normal distributions, as these are well-documented in the literature [7] and typically employ inverse Fourier transform-based approaches.

This paper presents a novel decomposition-based data augmentation method for multivariate time series that combines multivariate variational mode decomposition with conventional augmentation techniques. The first section establishes the theoretical foundations of multivariate variational mode decomposition, traditional augmentation methods, and synthetic data validation criteria. The second section details the proposed decomposition-based augmentation approach. The third section demonstrates method verification using actual sensor data.

## 2. THEORETICAL FRAMEWORK

### *2.1. Multivariate Variational Mode Decomposition*

The multivariate variational mode decomposition (MVMD) was developed by the authors of [8] as an extension of the variational mode decomposition algorithm (VMD) [9].

VMD represents a fully adaptive and non-recursive algorithm for time-frequency signal analysis. The fundamental assumption of this method posits that any original signal $f$ can be decomposed into a finite number $K$ of modes $u_k$ (intrinsic mode functions — IMFs), each characterized by central frequencies $\omega_k$ and limited bandwidths.

The signal decomposition through VMD is formulated as a constrained variational optimization problem:

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

subject to the constraint: $\sum\limits_{k=1}^{K} u_k\left(t\right) = f$ where $\{u_k\}$ and $\{\omega_k\}$ denote the sets of modes and their corresponding central frequencies; $\delta$ represents the Dirac function; $j_2 = -1$; $\|\cdot\|_2$ indicates the vector norm; $\omega_k$ denotes the central frequency; $*$ denotes the convolution integral; each mode $u_k\left(t\right) = A_k\left(t\right)\cos\left(\phi_k\left(t\right)\right)$ consists of an amplitude envelope $A_k$ and phase $\phi_k$. The unconstrained form of Equation (1), incorporating the augmented Lagrangian method, can be expressed as:

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

where $L$ represents the augmented Lagrangian function, $\lambda$ denotes the Lagrange multiplier, $\langle a, b\rangle$ indicates the scalar product of $a$ and $b$.

The solution is obtained through iterative optimization of $u_k^{n+1}$, $\omega_k^{n+1}$, and $\lambda_k^{n+1}$ using the alternating direction method of multipliers (ADMM) [10]. The final VMD formulation comprises:

$$\hat{u}_k^{n+1}\left(\omega\right) = \frac{\hat{f}\left(\omega\right) - \sum\limits_{i<k} \hat{u}_i^{n+1}\left(\omega\right) - \sum\limits_{i>k} \hat{u}_i^{n}\left(\omega\right) + \hat{\lambda}^n\left(\omega\right)/2}{1 + 2\alpha\left(\omega - \omega_k^n\right)^2}, \tag{3}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left|\hat{u}_k^{n+1}\left(\omega\right)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}\left(\omega\right)\right|^2 d\omega}, \tag{4}$$

$$\hat{\lambda}^{n+1}\left(\omega\right) = \hat{\lambda}^n\left(\omega\right) + \tau \left[ \hat{f}\left(\omega\right) - \sum_k \hat{u}_k^{n+1}\left(\omega\right) \right], \tag{5}$$

where $\wedge$ denotes the Fourier transform; $n$ represents the iteration number; $\alpha$ is the quadratic penalty coefficient; $\tau$ indicates the time step.

The MVMD method extends VMD by enabling the alignment of common frequencies across multiple synchronized signals (C). This capability proves particularly valuable in numerous scientific and engineering applications.

### *2.2. Augmentation by Magnitude Warping and Window Warping*

The magnitude warping augmentation algorithm modifies signal amplitudes within a specified window through multiplication by random scalars [2]. This amplitude transformation is implemented by convolving the data window with a smooth curve varying around unity. The method's key parameters include: ($\sigma$) the root mean square value of random noise, ($knots$) the number of control points defining the smooth warping curve [11].

The window warping augmentation algorithm distorts data within a randomly selected time series window through either expansion or compression (Fig. 1) [3]. The primary parameter governing this method is the original window size.

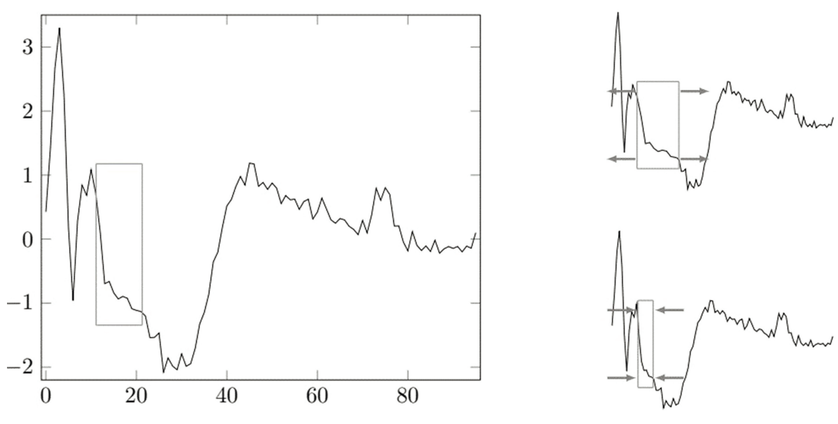


**Fig. 1.** Expanding and compressing data in the selected window.

### *2.3. Criteria for Evaluating Synthetic Data Adequacy*

Currently, no universal standards exist for assessing data augmentation algorithm quality. The development of appropriate metrics for evaluating synthetic data quality and diversity remains an open research question [12].

The most widely adopted criterion for synthetic data validation is the mean absolute error (MAE):

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}, \tag{6}$$

where $y_i$ represents the synthetic data set, $x_i$ denotes the original dataset, and $n$ indicates the time series length.

Alternative approaches employ neural networks for quality assessment. Yoon et al. [13] proposed evaluating synthetic data quality using a discriminative model comprising a two-layer LSTM network trained on original data. Similarly, Esteban et al. [14] developed a quality metric based on the mean absolute error of predictions from models trained on synthetic data.

For our analysis, we employ MAE while additionally comparing: probability density functions (PDFs) of original and synthetic processes; key statistical parameters (kurtosis and skewness).

## 3. PROPOSED METHOD FOR DATA AUGMENTATION

We present a novel decomposition-based data augmentation method designed to synthesize multivariate datasets while preserving critical time series characteristics, including trends and outliers. From an applied perspective, industrial applications typically involve synchronous data acquisition from heterogeneous sensors, which subsequently serve as input for neural network models. However, existing augmentation methods predominantly treat each signal independently, generating statistical processes that mimic individual signals while disregarding inter-signal relationships. This approach may introduce artifacts that compromise subsequent analysis.

Consider the example of process temperature sensor data (Fig. 2), where all sensors exhibit a temperature drop within the time interval $(3.8 \ldots 4.3) \cdot 10^4$ minutes, corresponding to equipment shutdown. This shared temporal feature must be preserved during synthetic data generation.

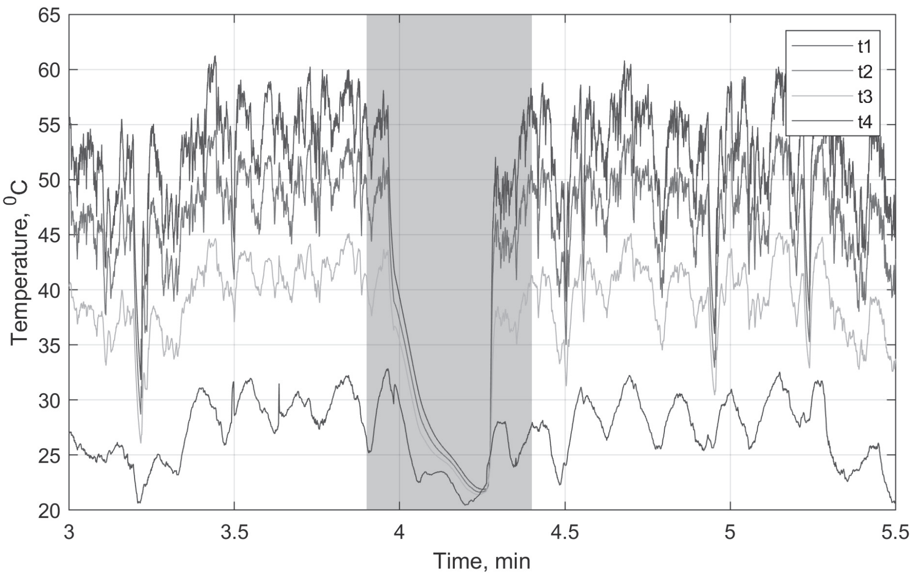


**Fig. 2.** Example of temperature change implementation with equipment shutdown zone.

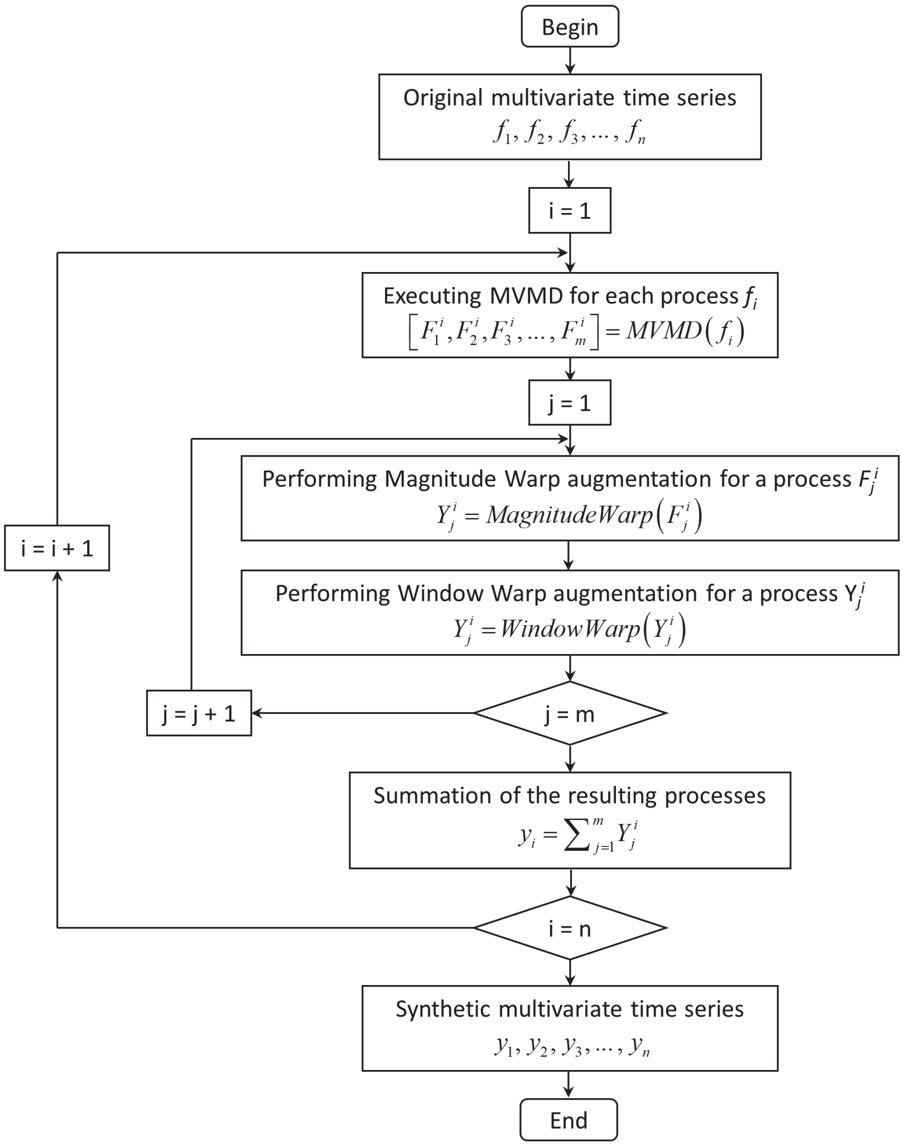


**Fig. 3.** Flowchart of the decomposition augmentation algorithm.

Furthermore, the relative temperature hierarchy $t1 > t2 > t3 > t4$ must be maintained throughout the augmented dataset.

Our decomposition-based augmentation method employs multivariate variational mode decomposition (MVMD) to separate each source signal into constituent modes (narrowband processes) with simpler structures. We then apply conventional augmentation techniques — magnitude warping and window warping — independently to each mode. Finally, we reconstruct the augmented signal by summing the processed modes, yielding synthetic multivariate datasets. Figure 3 presents the complete algorithm flowchart.

Like all augmentation methods, our approach incorporates several tunable parameters that significantly influence the results:

(1) MVMD Parameters:

- The number of decomposition modes ($m$) must be carefully selected based on signal non-stationarity and length. For typical applications, we recommend 4–6 modes.

- The first (low-frequency) mode may remain unaugmented to preserve global signal structure, or alternatively, may undergo augmentation with reduced intensity.

(2) Conventional Augmentation Parameters:
- Magnitude Warp: ($\sigma$) Standard deviation of Gaussian noise, ($knots$) Number of control points for the smoothing curve.
- Window Warp: ($window\ ratio$) Size of the original window, ($scales$) Distortion factor for window expansion/compression.

The selection of magnitude warping (for amplitude modification) and window warping (for temporal distortion) provides comprehensive signal transformation capabilities across both amplitude and time domains.

## 4. EVALUATION OF THE APPLICABILITY OF THE PROPOSED METHOD

### *4.1. Sensor Data Characteristics*

The proposed decomposition-based augmentation method was validated using temperature monitoring data acquired from multiple bearing support sensors in industrial equipment [15]. As shown in Fig. 4, the dataset comprises four synchronized time series with a sampling frequency of 1 minute, spanning 27 hours of continuous operation, with each signal containing 10 000 data points. The temporal synchronization of the acquisition system ensures consistent representation of trends and behavioral patterns across all measurement channels.

### *4.2. Augmentation Results and Validation*

Implementation of the decomposition augmentation algorithm with the parameters specified in Table 1 yielded synthetic temperature data that maintains several critical characteristics of the original dataset. By deliberately excluding augmentation of the first low-frequency MVMD mode, we preserved the fundamental structure of the time series while introducing controlled variations in other frequency components.

**Table 1.** Parameters of decomposition augmentation

| MVMDe | Magnitude-Warp | | Window-Warp | |
|---|---|---|---|---|
| Number of modes, units | Sigma, units | Knots, units | Window ratio, units | Scales |
| 6 | 0.2 | 10 000 | 0.5 | [0.5 4.0] |

The synthetic data successfully maintains both the characteristic temperature drop corresponding to equipment shutdown events and the consistent temperature hierarchy $t1 > t2 > t3 > t4$ throughout the generated dataset. Comparative analysis of the original and synthetic signals (particularly evident in Fig. 6 for channel $t1$) demonstrates effective preservation of global trends while introducing natural variability in oscillation characteristics, including both amplitude and frequency components.

Statistical evaluation reveals close agreement between original and synthetic datasets. The probability density functions shown in Fig. 7 exhibit similar distributions, with root mean square values differing by less than 1%. The kurtosis and skewness parameters show deviations within 14% and 16% respectively, while maintaining the essential characteristics of the original signals. Quantitative assessment using mean absolute error yields values of 0.06 (6%) for $t1$ and $t2$, 0.04 (4%) for $t3$, and 0.02 (2%) for $t4$, confirming the method's accuracy.

The critical advantage of the MVMD-based approach becomes particularly evident when comparing direct augmentation with the proposed decomposition method (Fig. 8). While conventional

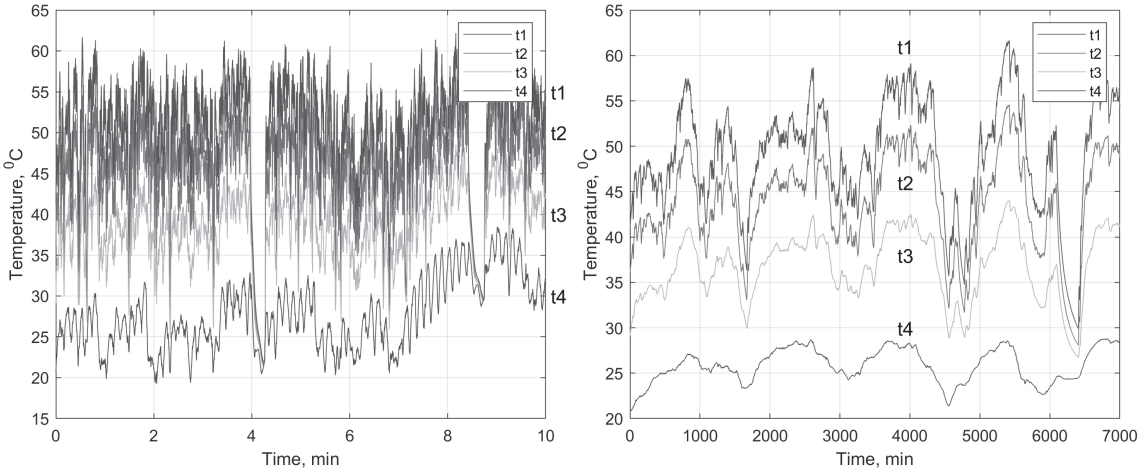


**Fig. 4.** Implementations of signals from temperature sensors (left) and an enlarged fragment of the implementations (right).

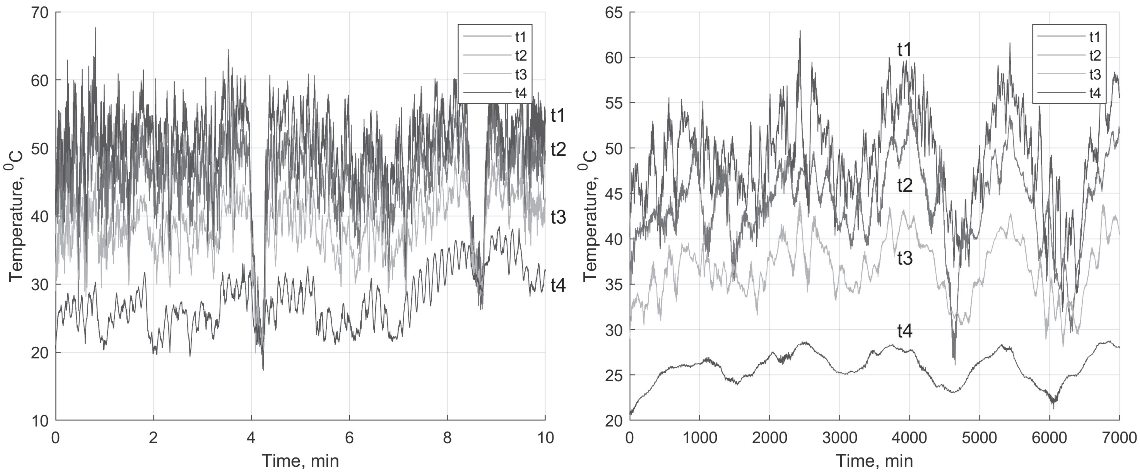


**Fig. 5.** Implementations of synthetic signals from temperature sensors (left) and an enlarged fragment of the implementations (right).

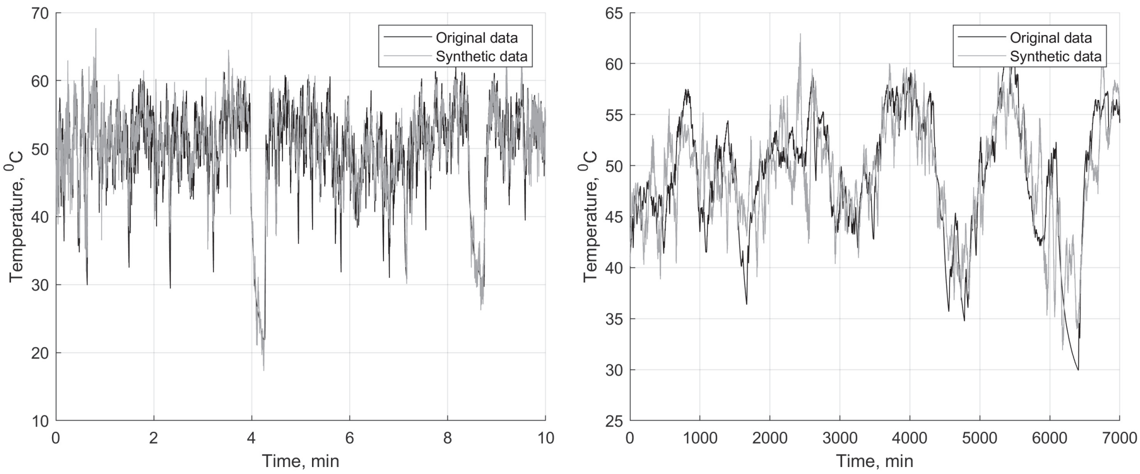


**Fig. 6.** Implementations of the original signal and the first synthetic signal (t1) from the multivariate data set (left) and an enlarged fragment of the implementations (right).

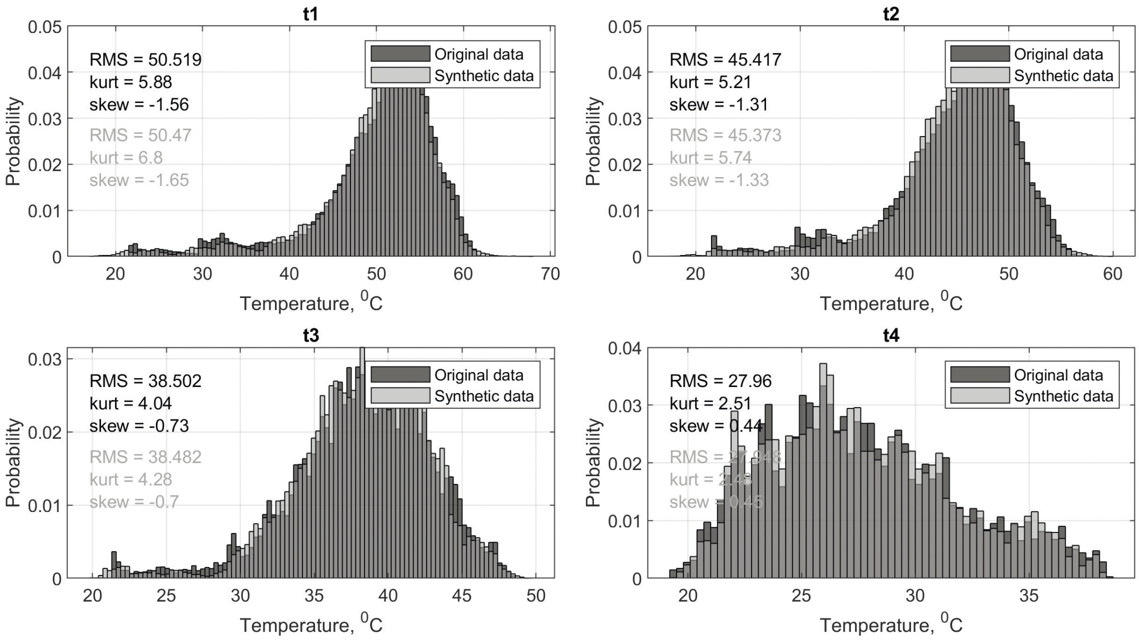


**Fig. 7.** Distribution densities of original and synthetic signals and their statistical characteristics.

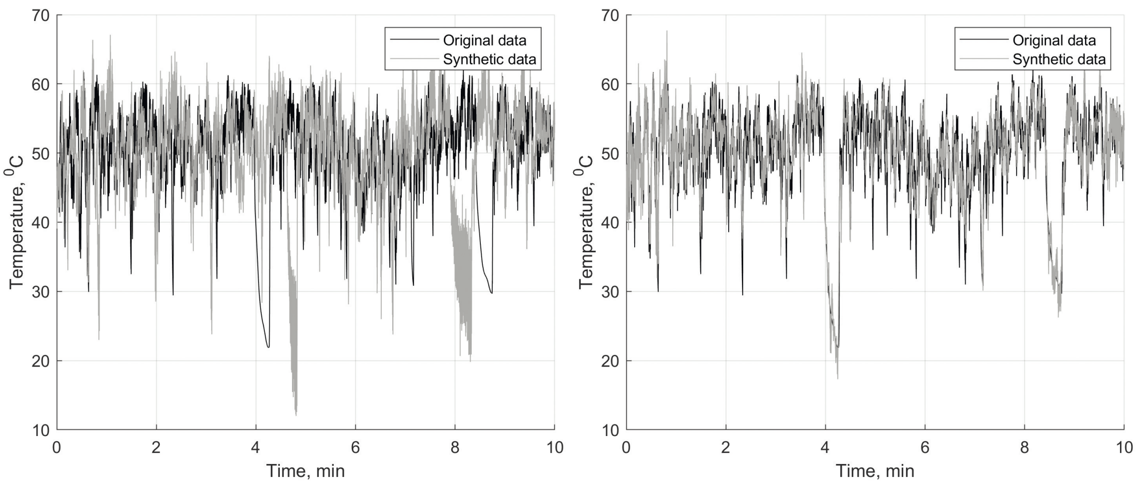


**Fig. 8.** The original signal and the first synthetic signal (t1) from the multivariate data set without preliminary decomposition of signals (left) and with decomposition (right).

augmentation fails to maintain temporal alignment and characteristic features, our method successfully preserves both synchronized events and global signal properties, demonstrating its superior performance for multivariate time series augmentation.

## 5. CONCLUSION

This study has presented an innovative decomposition-based approach for augmenting multivariate time series data, combining multivariate variational mode decomposition with conventional augmentation techniques. The developed method fundamentally advances current capabilities by preserving critical temporal characteristics while maintaining synchronization across multiple sensor signals — a crucial requirement for industrial monitoring applications where data from heterogeneous sensors must remain temporally aligned.

Through experimental validation using real-world temperature sensor data, we have demonstrated the method's ability to maintain both global data structure and precise inter-sensor relationships. The synthetic data preserves required operational characteristics such as the temperature hierarchy while introducing appropriate variability, with quantitative analysis confirming close agreement through mean absolute error metrics ranging between 2–6%. Statistical evaluation further substantiates the method's effectiveness, showing minimal deviations in key parameters including root mean square values (under 1% difference), kurtosis (within 14% variation), and skewness (below 16% deviation).

The comparative analysis provides compelling evidence for the necessity of the MVMD preprocessing stage, clearly demonstrating its superiority over direct augmentation approaches in preserving synchronized events and temporal relationships within multivariate datasets. This capability proves particularly valuable for industrial condition monitoring systems where maintaining temporal correlations between sensor signals is paramount for accurate diagnostics and predictive maintenance.

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