Energy Reports 8 (2022) 8805–8820

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Decomposition-based wind power forecasting models and their boundary issue: An in-depth review and comprehensive discussion on potential solutions

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ARTICLE INFO

Article history:
Received 2 April 2022
Received in revised form 12 June 2022
Accepted 1 July 2022
Available online 8 July 2022

Keywords:
Wind power prediction
Time series forecasting
Decomposition-based model
Boundary issue
Wavelet transform
Empirical mode decomposition

ABSTRACT

Recently, numerous forecasting models have been reported in the wind power forecasting field, aiming for reliable integration of renewable energy into the electric grid. Decomposition-based hybrid models have gained significant popularity in recent years. These methods generally disaggregate the original time series data into sub-time-series with better stationarity, and then the target data is predicted based on the sub-series. However, existing studies usually utilize future data during the decomposition process and therefore cannot be appropriately employed for real-world applications, due to the inaccessibility of future data. This problem is usually known as the boundary issue. By ignoring the boundary issue during decomposition, the developed decomposition-based forecasting models will inevitably lead to unrealistically high performance than what is practically achievable. These impractical predictions would compromise the scheduling and control decisions made based on them. In light of this, this study provides an in-depth review of decomposition-based models for wind power forecasting, as well as the existing solutions for resolving the boundary issue. We first categorize decomposition-based models with the consideration of the boundary issue, wherein the treatment of the boundary issue varies over different hybrid model architectures (i.e., direct approach and multi-component approach) and decomposition techniques (i.e., empirical mode decomposition, variational mode decomposition, wavelet transform, singular spectrum analysis and hybrid decomposition). Then, we systematically summarize commonly available boundary issue solutions into three categories, namely algorithm-based solutions, sampling-strategy-based solutions and iteration-based solutions. We also evaluate the strengths and limitations of the existing boundary issue solutions and discuss their applicability to different classification of decomposition-based models for wind power forecasting. This study will provide useful references for a wide range of future studies for developing accurate and practical wind power forecasting models.

Contents

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https://doi.org/10.1016/j.egyr.2022.07.005

Acronyms

ARIMA	Autoregressive Integrated Moving Average
AT	À trous algorithm
CEEMD	Complete Ensemble Empirical Mode Decomposition
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
CNN	Convolutional Neural Network
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Dec
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
ESN	Echo State Network
EWT	Empirical Wavelet Transform
ICEEMDAN	Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
IMF	Intrinsic Mode Function
KNN	K-Nearest Neighbor
LS-SVM	Least-Squares Support Vector Machine
LSTMNN	Long Short Term Memory Neural Network
MODWT	Maximal Overlap Discrete Wavelet Transform
MOGWO	Multi-Objective Grey Wolf Optimizer
NWP	Numerical Weather Prediction
SSA	Singular Spectrum Analysis
STACK	Stacking-Ensemble Learning
SVM	Support Vector Machine
VMD	Variational Mode Decomposition
WNN	Wavelet Neural Network
WPD	Wavelet Packet Decomposition
WT	Wavelet Transform

1. Introduction

1.1. Wind power forecasting

With the depletion of reserves of fossil fuels and increase of environmental pollution, exploring renewable and clean energy sources becomes critical and urgent (Guo et al., 2012). As an important type of clean renewable energy, wind energy has seen a significant increase of its installed capacity (Li et al., 2020). In this respect, the increasing uptake of wind energy affects the reliability of the grid due to the intermittent and stochastic nature of wind power generation. Therefore, a robust and accurate wind power prediction approach is the key to ensuring reliable wind energy integration (Shi et al., 2013).

Many methods have been developed to forecast wind power, from a few minutes to a few days into the future (Qian et al., 2019). Existing approaches can be categorized into four classes, namely persistence method, physical approach, statistical approach and hybrid model (Qian et al., 2019; Soman et al.). The persistence method is based on the assumption that the wind power at time $t + k$, where k refers to the prediction horizon, will be the same value at time t, which can be mathematically expressed as: $P(t + k) = P(t)$. The physical approach, which is also denoted as the Numerical Weather Prediction (NWP), uses weather parameters including wind speed, wind direction, atmospheric pressure, temperature and humidity in the mathematical models and predict wind power (Yan et al., 2015; Soman et al.; Qian et al., 2019). The statistical approach fits the measurement data into a model and tunes the model parameters via the difference between the predicted and actual wind power values. This approach does not depend on any prior knowledge, but depends on the pattern embedded in the data (Soman et al.; Wang et al., 2011). The statistical approach usually accepts two types of inputs, i.e., NWP data and historical data (Qian et al., 2019). The latter is also known as time series data in the computer science field. A number of common statistical methods have been reported, including the Support Vector Machine (SVM) (Liu et al., 2012), Autoregressive Integrated Moving Average (ARIMA) (Yatiyana et al., 2017), Multilayer Perceptron (Yeh et al., 2014), and Long Short Term Memory Neural Network (LSTMNN) (Shahid et al., 2021). The hybrid model generally combines different approaches to overcome the deficiencies of the constituents to improve its prediction performance (Tascikaraoglu and Uzunoglu, 2014). As an example, Li et al. (2020) used the wavelet decomposition approach to transform the wind power historical data into more stationary sub-sequences. In their study, SVMs were used to predict each sub-series. Then, the predictions of sub-series were aggregated to produce the final prediction value, which has achieved a better forecasting accuracy as compared with the use of SVM without decomposition. This type of hybrid model is also known as the decomposition-based hybrid model.

1.2. Decomposition-based hybrid models

Recently, the aforementioned decomposition-based hybrid models, which take advantage of the decomposition techniques, appear more and more often in the literature for time series forecasting in various applications, including wind power (Mbuli et al., 2020; Li et al., 2022b). An important reason for this is that the wind power time series data is usually non-stationary, nonlinear and noisy. It is thus hard to model such time series data using a single statistical model. With decomposition techniques, the non-stationary time series data can be transformed into a group of component sequences with different frequencies (Wu and Wu, 2021). Then statistical methods can be used to extract simpler patterns within the sub-series data (Salles et al., 2019). Moreover, decomposition techniques work well with combination technologies, i.e., using different forecasting methods to predict different sub-series, in order to improve forecasting accuracy (Clemen, 1989). For example, Zhang et al. (2019a) disaggregated the wind power time series into component series with different frequencies using the Variational Mode Decomposition (VMD) method. Then, the Least-Squares Support Vector Machine (LS-SVM), autoregressive moving average model and back propagation neural network were employed to forecast low-, medium- and high-frequency sub-series, respectively.

1.3. Boundary issue

In the current literature, many decomposition-based models have been incorrectly developed; therefore they are not able to be appropriately utilized to perform real-world forecasting tasks. The incorrect development of decomposition-based models occurs owing to the inclusion of future data to obtain the current decomposition values, which is practically impossible in real-world applications. This issue is generally denoted as the boundary issue (Quilty and Adamowski, 2018; Qian et al., 2019; Yu et al., 2001; Kaufman et al., 2012). To be more specific, some existing decomposition-based hybrid models, e.g., Wang et al. (2016) and Guo et al. (2012), tend to firstly decompose the entire time series dataset into component sequences. Then, each sub-series is split into training and test datasets. The training and test processes are performed in a rolling-horizon fashion. For instance, suppose the input and output sizes of the forecasting model are k and 1, the first k data samples in the component training or test dataset is used to predict the $(k+1)$th data. Then the second to the $(k+1)$th data samples are used to predict the $(k+2)$th data and so on. For each sub-sequence, the training dataset is used to build the forecasting model, while the test dataset is used for evaluation. In this procedure, future data samples are accessed in the decomposition phase, which is not possible in practice. Suppose the current time point is time t; the time series to be disaggregated should only contain the data samples up to time t. The reason is that the data after time t is future data and unknown. However, in the aforementioned decomposition procedure, the entire time series, including the time series data after the current time instance, is decomposed together, leading to an ambiguous boundary between the available data and unknown data at a specific time point.

Specifically, the boundary issue can cause errors in a forecasting model in four distinct ways:

- *Future data leakage*: Time series data belonging to the future time ($> t$) is utilized in the computation of sub-series at time t.
- *Incorrect partition of data into training and test datasets*: As the entire time series is decomposed first and then split into training and test datasets, the component series in the training dataset may contain information from the time series data that belongs to the test dataset.
- *Inappropriate selection of decomposition levels*: Since time series data with a longer horizon and more complex frequency domain is usually more suitable to be decomposed into more components, decomposing the entire time series causes the model to select higher decomposition levels than achievable in practice (Quilty and Adamowski, 2018).
- *Unrealistic boundary effect*: The boundary effect usually refers to the distortion of decomposition caused by missing data samples before the first time series data sample and after the last time series data sample. If the entire time series is decomposed, the data samples at the middle part of the time series are not susceptible to the boundary effect, which is different from what would happen in practice (Xiong et al., 2014; Nie et al., 2020; Feng and Shu; Meng et al., 2019; Rana and Koprinska, 2016).

Most of the studies have been conducted from a pure machine learning point of view, focusing on the development of novel decomposition-based hybrid methods. These studies thus do not offer useful engineering and practical implications. When future data is incorporated in the forecasting model and the boundary issue is disregarded in decomposition process, the resulting models usually cause misleading and over-estimated performances than what is realistically achievable (Quilty and Adamowski, 2018). In renewable energy integration, power system scheduling is expected to be conducted based on predicted renewable energy. In this respect, an unrealistically good prediction model of wind power can lead to serious issues pertaining to power systems reliability on the dispatch day (Wen et al., 2022; Yuan et al., 2022).

1.4. Related studies

Researchers have studied the boundary issue and proposed some feasible solutions. Quilty and Adamowski (2018) discussed the boundary issue of the wavelet-decomposition-based hydrological forecasting models. They introduced a new forecasting framework based on the AT and Maximal Overlap Discrete Wavelet Transform (MODWT) to resolve this problem. Nguyen and Nabney (2010) employed a specific wavelet family, i.e., the Haar wavelet, to address the boundary issue in electricity demand prediction.

Decomposition-based wind power forecasting models have been reviewed previously. Tascikaraoglu and Uzunoglu (2014) categorized the hybrid models into four classes, i.e., combined approaches with data pre-processing techniques (i.e. decomposition-based hybrid models), weighting-based combined approaches, combined approaches with parameter selection and optimization techniques, as well as combined approaches with error processing techniques. Each subclass of hybrid models has been reviewed, with their advantages and limitations discussed in detail. The decomposition-based hybrid models have been evaluated as a suitable method for time series forecasting tasks with long prediction and non-stationarity. Qian et al. (2019) reviewed the decomposition-based hybrid models available in recent years. The models are grouped into three classes based on the decomposition techniques used. According to the fact that Empirical Mode Decomposition (EMD) and Wavelet Transform (WT) are the most widely used decomposition techniques in hybrid models, the decomposition-based models are categorized into (i) WT-based models, (ii) EMD-based models and (iii) models based on other decomposition techniques. In this paper, the boundary issue is considered as one of the main challenges yet to be resolved in the field of decomposition-based wind power forecasting.

It is noteworthy that the existing review papers have only focused on the evaluation, classification, comparison and discussion on decomposition-based models available in the literature. These reviews have ignored the fact that without addressing the boundary issue, the proposed decomposition-based models therein are unable to be applied to real-world forecasting tasks (Quilty and Adamowski, 2018). To the best of our knowledge, there has been no reported study on (i) a systematic discussion focusing on the boundary issue in decomposition-based wind power forecasting models; and (ii) an in-depth review of the feasible solutions to handle the boundary issue. This paper aims to bridge this research gap between pure methodical research on prediction and applied research in wind power forecasting, thus providing practical references for future wind power forecasting models.

1.5. Main contributions of the paper

The main contributions of this paper are twofold:

- A systematical review on decomposition-based wind power forecasting models in recent years from the perspective of boundary issue treatments.
- An in-depth review of the feasible solutions to address the boundary issue, along with critical discussions of their advantages and disadvantages.

Note that as the available studies on resolving the boundary issue in wind power forecasting are still limited, our review covers not only the wind power forecasting area, but also other domains where feasible solutions to undertake the boundary issue have been reported.

1.6. Structure of the paper

The remainder of this paper is organized as follows. Section 2 reviews the commonly used decomposition-based hybrid models for wind power forecasting based on different architectures and decomposition techniques. The existing boundary issue solutions in wind power studies are also listed. Section 3 provides a comprehensive review on the feasible boundary issue solutions, along with their advantages, disadvantages and effectiveness. A comparative discussion is given in Section 4, and suitable application scenarios of each solution are presented. Finally, concluding remarks are given in Section 5.

2. Decomposition-based models for wind power forecasting

In this review, decomposition-based prediction models for wind energy applications are surveyed, with a focus on the treatment of the boundary issue. The general procedure of decomposition-based forecasting models for wind power forecasting can be divided into six stages, as follows:

- *Data pre-processing*: Conduct operations such as data cleaning, filling missing data and normalization to process time series data, with the aim of improving the forecasting performance (Çevik et al., 2019).
- *Decomposition*: Disaggregate the original non-stationary and nonlinear time series to generate the component sequences with more stationary properties. Common decomposition approaches include EMD, VMD, WT, etc.
- *Forecasting*: Forecast the target wind power data based on the decomposed time series data. The Convolutional Neural Network (CNN) (Yildiz et al., 2021), LSTMNN (Duan et al., 2021), Echo State Network (ESN) (Hu et al., 2021), etc., are used in the literature of decomposition-based wind power forecasting models.
- *Optimization*: Leverage some automatic methods to select suitable decomposition techniques or forecasting models and optimize the model hyper-parameters. Some popular optimization techniques, which include Multi-Objective Flower Pollination Algorithm (Wu et al., 2020; Qu et al., 2019) and Multi-Objective Grey Wolf Optimizer (MOGWO) (Hao and Tian, 2019), are applied to improve the performance.
- *Error correction*: Predict forecasting errors and combine them with the predicted value obtained in the forecasting phase to yield the final prediction. Only a limited number of studies have employed the error correction mechanism in their models (Deng et al., 2020; Hao and Tian, 2019).
- *Uncertainty estimation*: Analyze the wind power distribution and provide the upper and lower boundaries of the target wind power data instead of a single value. Similar to error correction, only a limited number of studies have included uncertainty estimation into their wind power forecasting models (Xiang et al., 2020; Liu and Duan, 2020).

The boundary issue is caused by incorrect operations during the decomposition phase. Therefore, decomposition-based forecasting models for wind power applications are classified and reviewed from the perspective of decomposition techniques. In this respect, the structures of decomposition-based models have a significant impact on the boundary issue treatment. Hence, the decomposition-based wind power forecasting models are categorized and analyzed based on their architectures as well. In addition, the available boundary issue solutions pertaining to decomposition-based wind power prediction models are reviewed and discussed.

2.1. Classifications of decomposition-based forecasting models based on architectures

In general, studies of decomposition-based models in the literature focus on the decomposition and forecasting modules, which can be categorized into two classes: direct approach and multi-component approach (Nguyen and Nabney, 2010; Qian et al., 2019). A significantly more number of papers studying the multi-component approach than the direct approach due to the fact that the multi-component approach can fit the various patterns of sub-series with different frequencies.

2.1.1. Direct approach

The direct approach disaggregates the original time series data into several sub-series, and builds a single forecasting model using the sub-sequences as the input variables (explanatory variables) to directly predict the target variables (Yin et al., 2019). Fig. 1 shows that the structure of the direct approach. Compared with the multi-component approach, the direct approach only requires one forecasting model. Moreover, while the multi-component approach can only extract the temporal patterns from each component series, the direct approach explores not only the temporal relationships but also other relationships among different sub-series. However, the forecasting model of the direct approach needs to be able to handle multi-dimensional input data. As a result, the CNN is commonly employed as the forecasting model of the direct approach due to its ability to handle multi-dimensional data. The deep residue CNN model (Yildiz et al.,

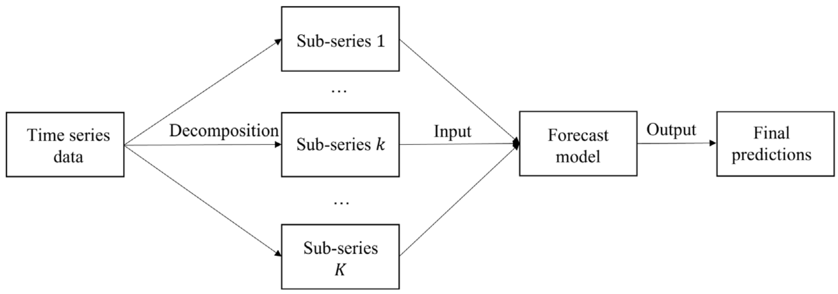

Fig. 1. Direct approach.

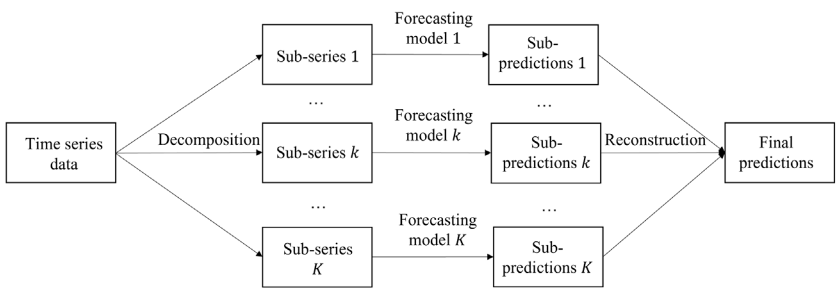

Fig. 2. Multi-component approach.

2021) and two-dimensional CNN model (Abedinia et al., 2020a) are commonly used forecasting models in the direct approach literature. Yin et al. (2019) proposed a cascaded CNN-LSTMNN model. It uses the CNN to extract features from multi-dimensional input data and utilizes the LSTMNN to make the prediction.

2.1.2. Multi-component approach

The multi-component approach decomposes the original time series data into several sub-series before fitting it into prediction models. Then, different models are implemented to forecast different component series and the component predictions are reconstructed into the target prediction (Altan et al., 2021; da Silva et al., 2021). Fig. 2 shows the multi-component architecture has a more flexible architecture because different forecasting models can be employed based on the characteristics of different component series. Moreover, there is no requirement to handle multi-dimensional data in the forecasting models. Hence, most of the traditional time series forecasting methods can be applied in the multi-component approach. Available forecasting models include the LSTMNN (Sun et al., 2021), Extreme Learning Machine (ELM), Fuzzy Neural Network, ENN, Radial Basis Function Neural Network (RBFNN), Generalized Regression Neural Network (GRNN) (Wu et al., 2020), Wavelet Neural Network (WNN), Bernstein polynomial model, SVM, Hermite Neural Network (Dong et al., 2021a), etc. After forecasting the sub-series, the sub-predictions are integrated to yield the final result. Superposition (Tian et al., 2021; Duan et al., 2021) and ELM (Hao and Tian, 2019) are generally used for reconstruction.

2.1.3. Discussions on different boundary issue treatments based on architectures

From the boundary issue perspective, there is a significant difference between the direct and multi-component approaches. During a single step of the training phase, the direct approach requires the decomposition of explanatory variables and the original value of target variables, while the multi-component approach needs the decomposition of both explanatory and target variables. It is thus easier for a direct approach to avoid involving future data in the decomposition phase when the sampling-strategy-based boundary issue solutions introduced in Section 3.2 are applied.

2.2. Classifications of decomposition-based forecasting models based on decomposition techniques

The decomposition techniques in the literature can be categorized into five sub-classes, i.e., EMD-based decomposition, WT-based decomposition, VMD, Singular Spectrum Analysis (SSA) and hybrid decomposition. Qian et al. (2019) reviewed the decomposition-based wind power forecasting studies before 2019 and found that EMD-based and WT-based methods were the most commonly used decomposition approaches. Recently, the VMD approach has received more attention due to its adaptivity and explicit mathematical theory. Moreover, numerous hybrid decomposition approaches have been reported in recent literature.

2.2.1. Wavelet transform-based forecasting models

WT is a widely used time series decomposition technique. It inherits and develops the decomposition methods based on the Fourier transform (FT). The commonly used FT-based decomposition approaches, which include fast Fourier transform and short-time Fourier transform, suffer from certain limitations, e.g., inability to handle non-stationary time series and keeping a constant resolution for all frequencies. WT addresses the aforementioned drawbacks by using an orthogonal wavelet basis as the basis functions instead of the sine and cosine waves used in FT (Peng and Chu, 2004). The principle of WT is to disaggregate the original time series into several high-frequency detail sub-series and a low-frequency approximation sequence using a set of high-pass and low-pass filter pairs (Li et al., 2020). The decomposition procedure is presented in Fig. 3, where A, D, L, H represent the approximation, detail, low-pass filter and high-pass filter respectively, and the decomposition level is equal to 3. To obtain the approximation and detail coefficients at each level, the wavelet and scaling functions are computed based on a given wavelet basis, which is composed of a mother wavelet and father wavelet. The mother wavelet or preceding wavelet function is shifted and scaled by the power of two to generate the succeeding wavelet function. The relation is described as

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k\cdot 2^j}{2^j}\right), \tag{1}$$

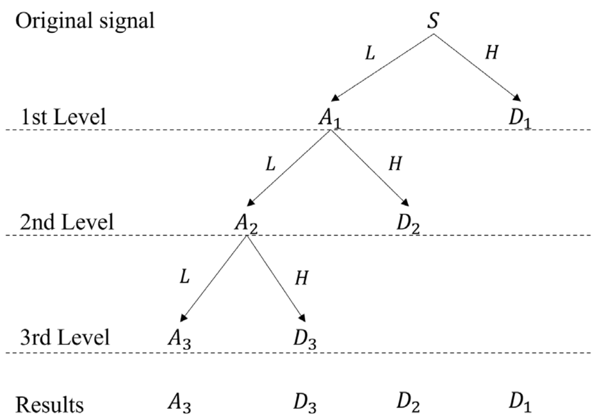

Fig. 3. Illustration of wavelet transform (Qian et al., 2019).

where ψ is the mother wavelet or preceding wavelet, and j, k denote the scale and shift parameters respectively. Then, the detail part can be obtained by a convolution process as follows

$$\gamma_{j,k} = \int_{-\infty}^{\infty} x(t)\psi_{j,k}(t)dt. \tag{2}$$

The approximation part and scaling function can be computed based on the same idea, while the mother wavelet is replaced by the father wavelet. Several WT-based forecasting models, including WT-based SVM model, WT-based ESN model and WT-based two dimensional CNN model, have shown better performance compared to the non-decomposition-based benchmark models, with the help of Atomic Search Optimization and Particle Swarm Optimization (Li et al., 2020; Wang et al., 2019; Abedinia et al., 2020a). Ding et al. (2021) proposed an extreme-point-based stop criterion to determine the suitable decomposition level of WT and improved the adaptability of WT. Based on this improved WT, an improved WT-based LS-SVM model optimized by genetic algorithm was introduced for short-term wind power prediction.

Two variants of WT have been reported in the wind power forecasting studies, i.e., Empirical Wavelet Transform (EWT) (Deng et al., 2020) and Wavelet Packet Decomposition (WPD) (Liu and Duan, 2020). The key concept of EWT is that the scaling and wavelet functions are determined based on the Fourier spectrum analysis over a specific time series, while the scaling and wavelet functions of classic WT are based on the selected wavelet basis with shifting and scaling operations and hence lack adaptivity (Gilles, 2013). As mentioned earlier, the classic WT decomposes the approximation part at each level to obtain the subsequent approximation and detail coefficients until the stopping criterion is met. In WPD, both approximations and details are further decomposed to yield the sub-series at the succeeding level. Fig. 4 presents an example of WPD. The new sub-series decomposed from the approximation and detail parts are named AA (approximation of the approximation), AD (approximation of the detail), DA (detail of the approximation) and DD (detail of the detail). The corresponding wind power studies have proven the validity and efficiency of these two WT-based decomposition techniques in wind power forecasting. For instance, an EWT-based Elman neural network (ENN) model was proposed by Deng et al. (2020), and an EWT-ARIMA model based on an error correction mechanism has been implemented to offset the forecasting errors of each sub-series and residual errors caused by the decomposition and reconstruction procedures. Liu and Duan (2020) presented a hybrid wind power forecasting model based on WPD, Outlier-Robust Extreme Learning Machine and

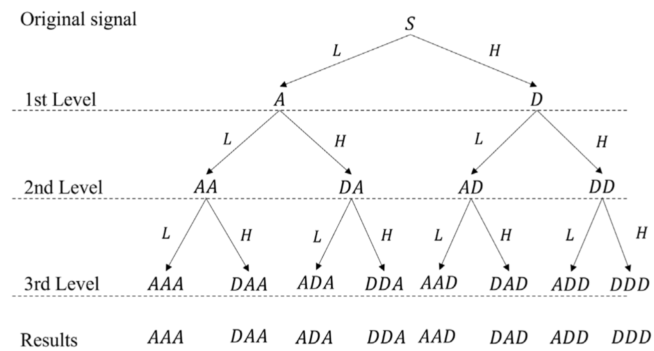

Fig. 4. Illustration of wavelet packet decomposition (Ocak et al., 2007).

Stacked Auto-Encoder. Moreover, Multi-Objective Grasshopper Optimization Algorithm, Ljung–Box Q-Test and Bivariate Kernel Density Estimation were implemented for optimization, error correction and uncertainty estimation, respectively.

2.2.2. Empirical mode decomposition-based forecasting models

Although WT has great advantages in handling non-stationary data, it has the limitation of non-adaptability. As a result, the wavelet basis and decomposition level need to be selected with caution, in order to ensure they are suitable for decomposing certain time series (Qian et al., 2019). Moreover, once the wavelet basis is determined, it cannot be replaced during the decomposition process. Even though the selected wavelet basis can achieve the best performance globally via some optimization approaches, it may not be suitable for some local parts of the time series. EMD, as an adaptive time series decomposition approach, can overcome these weaknesses. Instead of decomposing the time series into a group of approximation and detail components as in the WT, EMD tends to decompose the time series into a set of sub-series known as the Intrinsic Mode Functions (IMFs) and a residue based on the characteristics of the specific time series through a recursive sifting process. The underlying procedure is listed as follows (Huang et al., 1998):

1. Connect all the maxima and minima of the original signal $x(t)$ to obtain the upper and lower envelopes.
2. Calculate the mean of the upper and lower envelopes to get the mean envelope $m_1(t)$.
3. Calculate the first component $h_1(t) = x(t) - m_1(t)$.
4. Check if $h(t)$ satisfies the constraints of IMF. If so, this component is recorded as an IMF $c_1(t)$ and go to Step 5. Otherwise, this component is treated as the original time series and repeat Steps 1 to 4.
5. Use $x_1(t) = x(t) - c_1(t)$ as the new original time series and repeat Steps 1 to 4 to obtain new IMFs.

After the stopping criterion is satisfied, the process of splitting IMFs stops. The residue can be derived by $r(t) = x(t) - \sum_{i=1}^{k} c_i(t)$, where k denotes the number of IMFs. The residue $r(t)$ and the k IMFs $\{c(t)\}$ are the decomposed components obtained by the EMD. An EMD-based model is reported in wind power forecasting studies. Abedinia et al. (2020b) combined EMD, K-means clustering and Bagging Neural Network to predict wind power. K-means clustering was implemented to cluster the wind power datasets with similar patterns and then a hybrid model was trained for each data subset.

However, the straightforward implementation of the sifting procedure produces mode mixing, which refers to a time series of different frequency resolutions residing in one IMF or a time series of similar frequency resolutions existing in different IMFs, due to signal intermittency (Altan et al., 2021). To overcome this mode mixing issue, several EMD variants have been proposed, which include Ensemble Empirical Mode Decomposition (EEMD), Complete Ensemble Empirical Mode Decomposition (CEEMD), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN). The key idea of EEMD is introducing different realizations of the finite amplitude white noise into the decomposition process and taking the average of different outcomes from the same IMFs as the final result (Altan et al., 2021). This causes another issue, i.e., the reconstructed time series contains residual noise, which is addressed by CEEMD, CEEMDAN and ICEEMDAN with different approaches. In the wind power prediction literature, CEEMD and ICEEMDAN are the most commonly used. CEEMD is combined with the Bernstein polynomial model with a mixture of Gaussians to forecast wind power (Dong et al., 2021a). da Silva et al. (2021) proposed a CEEMD-based Stacking-Ensemble Learning (STACK) model for multi-step wind energy forecasting. The STACK consisted of two layers. Multiple forecasting models including K-Nearest Neighbor (KNN), Partial Least Squared Regression, Ridge Regression and Support Vector Regression with linear kernel were trained in the first layer. Then the prediction of each model was used as the input of the second layer to obtain the final prediction. Moreover, ICEEMDAN has been combined with the LSTMNN (Altan et al., 2021) and WNN (Du et al., 2019) to improve the performance of wind power forecasting.

2.2.3. Variational mode decomposition-based forecasting models

EMD is known for its recursive nature and lacks explicit mathematical theory. These drawbacks limit its robustness, rendering its effectiveness questionable in handling the issue of sensitivity in sampling. To address these drawbacks, VMD, as a complete non-recursive variational decomposition approach, which combines Wiener filtering, Hilbert transform and Alternating Direction Method of Multipliers, was proposed in Dragomiretskiy and Zosso (2013). The principle of VMD is to convert the original time series into a constrained variational problem before solving it. The resulting constrained variational problem can be represented as

$$\begin{aligned} & min\left\{\sum_{k=1}^{K}\left\|\partial(t)\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \\ & s.t.\sum_{k=1}^{K}u_k=f, \end{aligned} \tag{3}$$

where u_k refers to the kth IMF, $\partial(t)$ presents the partial derivative of the function for time t, $\delta(t)$ is the unit pulse function, j indicates the imaginary unit, $*$ denotes the convolution operation (Duan et al., 2022). Several studies have focused on applying VMD to address the non-stationarity of wind power time series data and have achieved significant improvement on the forecasting accuracy. The corresponding hybrid models combine the VMD with various forecasting models including the LSTMNN (Duan et al., 2021), Deep Belief Network (Duan et al., 2022), improved residual-based deep CNN (Yildiz et al., 2021), ESN (Tian et al., 2021; Hu et al., 2021), multi-kernel robust ridge regression model (Naik et al., 2019) and ELM (Hao and Tian, 2019). Moreover, a set of optimization techniques have been implemented for parameter tuning and model selecting, which include Particle Swarm Optimization (Duan et al., 2022), improved Whale Optimization Algorithm (Tian et al., 2021), Multi-Objective Chaotic Water Cycle Algorithm (Naik et al., 2019) and MOGWO (Hao and Tian, 2019).

2.2.4. Singular spectrum analysis-based forecasting models

SSA is a powerful time series analysis approach, which integrates time series analysis, multivariate statistics, multivariate geometry, dynamical systems and signal processing. SSA can decompose the original time series into trend, periodic oscillation, and noise. Generally, SSA comprises four steps containing embedding, singular value decomposition, grouping and diagonal averaging (Hassani, 2021). A hybrid model based on SSA and Laguerre neural network was introduced by Wang et al. (2020). The opposition transition state transition algorithm was employed for optimization, and a set of comparative experiments was implemented to demonstrate the outstanding performance of the proposed hybrid model.

2.2.5. Hybrid-decomposition-based forecasting models

The aforementioned decomposition techniques mainly suffer from two limitations. Firstly, the highest frequency component is generally hard to fit into the forecasting model. Secondly, the selection of decomposition techniques and their variants is usually performed empirically. To overcome both limitations, two types of hybrid decomposition methods have been reported in wind power forecasting research, i.e., secondary decomposition and model-selection-based decomposition.

The fundamental idea of **secondary decomposition** is to further decompose the most disordered component into several new sub-series. By doing so, the most unpredictable component is converted into a set of relatively steady components. As a result, the decomposed time series is easier to fit into the forecasting model. Several publications in the wind power forecasting field have utilized these novel decomposition techniques. Yin et al. (2019) proposed a wind power forecasting model based on the secondary decomposition. In this model, EMD was implemented to decompose the original wind power time series data into several IMFs, and then VMD was applied to further disaggregate the first IMF into a set of component series. In the hybrid model presented by Zhang et al. (2019b), the VMD was implemented to decompose the original time series into a set of sub-series, while sample entropy was applied to estimate the complexity of the obtained sub-sequences. Then, WPD was employed to further decompose the noisiest component into a set of component series with higher stationarity. Many reported studies have benefited from the secondary decomposition by following this concept. The models in the research attempts extract the high-frequency component and perform further decomposition to improve forecasting accuracy (Sun et al., 2021; Qu et al., 2019). Moreover, some secondary decomposition approaches extract the trend, i.e., the most stationary part, of time series, and then decompose the residue (Xiang et al., 2020; Mi et al., 2019; Li et al., 2022a). A representative example is the hybrid model proposed by Xiang et al. (2020). Accordingly, SSA was implemented to extract the trend of time series data and then VMD was applied to decompose the residue.

The **model-selection-based decomposition** selects the most suitable decomposition techniques from several candidate decomposition methods based on certain pre-defined evaluation criteria and methods. Yu et al. (2022) presented a complexity-trait-driven decomposition model selection strategy. Different decomposition techniques including EMD-based decomposition methods, Robust Local Mean Decomposition and VMD were applied to decompose the original time series data. Then the complexity trait metrics of the decomposed components were calculated based on several complexity trait testing approaches including sample entropy, approximate entropy, fuzzy entropy, permutation entropy and fractal dimension. After computation, the complexity trait of a specific decomposition approach could be obtained by weighting and summing the complexity-trait metrics of the corresponding components. Finally, the complexity traits were compared in order to find the most suitable decomposition technique. Another widely used strategy is to select a basic forecasting model and use the forecasting accuracy, which is obtained based on this basic learner, as the evaluation metrics of decomposition approaches (Çevik et al., 2019; Jaseena and Kovoor, 2021; Dong et al., 2021b). Jaseena and Kovoor (2021) employed Bidirectional LSTMNN as the forecasting model and selected WT, EMD, EEMD and EWT as decomposition techniques. The performance of the hybrid model was examined by standard deviation, root mean square deviation, mean absolute error, R^2, and coefficient of variation. Then the decomposition technique leading to the best performance was selected. Moreover, several studies have shown that secondary decomposition approaches can perform as candidates in the model-selection-based decomposition and lead to performance improvement (Wu et al., 2020; Liu et al., 2019).

2.2.6. Discussions on different boundary issue treatments based on decomposition methods

The aforementioned decomposition techniques can be categorized into two classes based on whether they have an explicit mathematical theory. A representative example of decomposition approaches without fixed mathematical models is EMD-based decomposition methods. EMD and its variants are based on a recursive sifting process. Due to the recursive nature of EMD and the fact that the positions of extrema highly depend on the time series itself, there is no fixed mathematical model for EMD.

The lack of fixed mathematical models causes more challenges when addressing the boundary issue. On the other hand, with fixed mathematical models, eliminating the future data usage of the algorithm becomes a potential solution. The simplest example is the moving average algorithm, which is based on the idea of using moving average filters to estimate the trend and seasonality in time series (Cleveland and Tiao, 1976). The mathematical expression of a moving average filter is

$$\hat{x}(t) = \frac{1}{2k+1} \sum_{i=-k}^{k} x_{t+i}, \tag{4}$$

where x_{t+i} refers to the time series data at time $t+i$, and $2k+1$ denotes the window size of the moving average filter. Obviously future data samples are accessed "illegally" (practically unachievable) in this equation as data samples from time $t-i$ to time $t+i$ is used to decompose data at time t. However, if the equation is modified to

$$\hat{x}(t) = \frac{1}{k+1} \sum_{i=-k}^{0} x_{t+i}, \tag{5}$$

the boundary issue can be resolved, but the decomposition quality is negatively affected. A similar idea has been applied to address the boundary issue in WT-based forecasting models (Quilty and Adamowski, 2018; Shensa et al., 1992).

2.3. Boundary issue treatments in decomposition-based models for wind power forecasting

In decomposition-based wind power forecasting, only a few studies have realized the boundary issue and adopt relevant measures. The solutions are mainly based on the rolling mechanism. Specifically, the entire training dataset is disaggregated into component time series. Then, one test data sample is forecast at a time. Once the test data sample has been predicted, it is treated as a known sample and then the new time series composed of training time series data and known test data samples is re-decomposed to obtain the new component series (Yu et al., 2022; Duan et al., 2022; Deng et al., 2020). Assume S is time series data with a length of N, M past observations are used to forecast the next target data sample, and the time series will be decomposed into C components. Table 1 shows the working principle of the rolling-mechanism-based sampling strategy, and Fig. 5 presents the actual practice of the rolling-mechanism-based sampling strategy. However, this solution can only partially address the boundary issue. Admittedly, by splitting the training and test datasets, information contained in the test dataset is kept from being leaked into the decomposition results of the training dataset. Moreover, incrementally predicting test data samples and re-decomposing the known time series can avoid the inclusion of future data in the test phase. Nevertheless, the future-data leakage problem still exists in the training phase as the entire training dataset is decomposed at the same time. To be more specific, in the training phase, the explanatory variables carry the information from the target variables due to the incorrect operation of decomposition. As a result, the model can utilize the leaked data to make unrealistically accurate predictions based on the training dataset. As the boundary issue is addressed in the test phase, the model trained in the context of data leakage cannot reproduce its performance on the test dataset. This issue is usually reported as data leakage in machine learning research (Kaufman et al., 2012). Although the aforementioned solution makes the test results reliable and consistent with the practical performance, the over-fitting problem arises as a result of the inconsistent boundary issue treatment in the training and test phases. As such, the rolling-mechanism-based solution cannot be defined as a complete solution for the boundary issue. In the next section, boundary issue solutions are reviewed in a more comprehensive manner. They are not limited to wind power prediction, in order to cover more potential choices to resolve the boundary issue in decomposition-based prediction models.

Table 1
Working principles of the rolling-mechanism-based sampling technique.

Dataset partition	Sample ID	Explanatory data	Target data
Training dataset	Sample 1 ... Sample P	Decompose $\{S_1, \ldots, S_{M+P}\}$	
Test dataset	Sample P+1 ... Sample N-M	Decompose $\{S_1, \ldots, S_{M+P}\}$ ... Decompose $\{S_1, \ldots, S_{N-1}\}$	S_{M+P+1} ... S_N

Sample k ($k \in [1, \ldots, N-1]$) is composed of M explanatory data and one target data.

3. Feasible solutions of the boundary issue

The core idea of addressing the boundary issue is to eliminate the misuse of future data during the decomposition process. As mentioned earlier, improving the algorithm based on mathematical theory of decomposition approaches is an alternative way to achieve this objective, and the moving average algorithm is a good example of this approach. Another commonly used method is to modify the sampling strategy, and a representative example is the rolling mechanism sampling strategy. Moreover, Yu et al. (2001) proposed an iterative approach to avoid the misuse of future data. This approach benefits from an improved sampling strategy. The essence of this solution is based on a convergence process achieved by iteration, so this method is categorized into a new class and discussed separately.

3.1. Algorithm-based boundary issue solutions

The algorithm-based approaches generally address the boundary issue based on the mathematical theory of decomposition

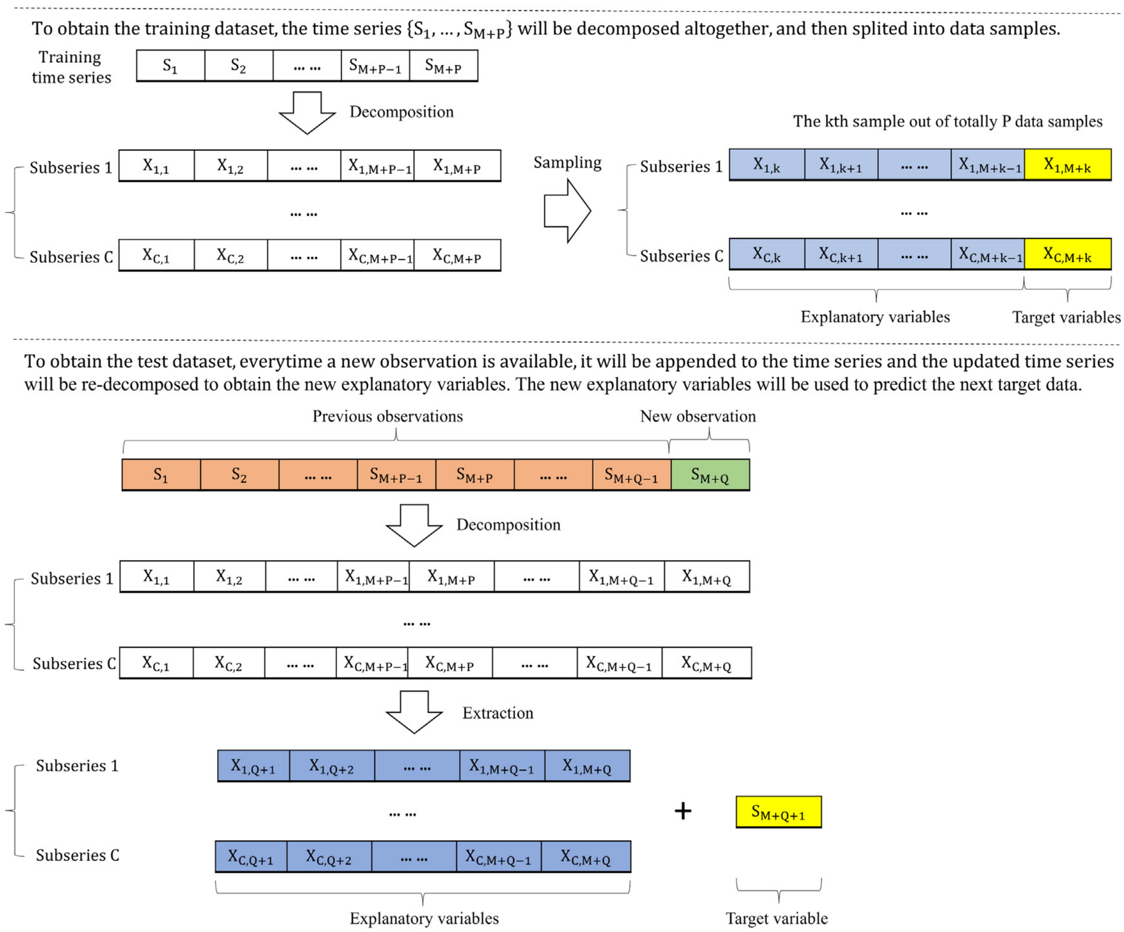

Fig. 5. Actual practices of the rolling-mechanism-based sampling technique.

techniques and the modification of the decomposition algorithm to avoid the misuse of future data. A significant constraint of this approach is that the mathematical model of the decomposition method needs to be predetermined. To be more specific, the decomposition process should not depend on the characteristics of a specific time series. A representative counterexample is the aforementioned EMD-based decomposition techniques. Moreover, some approaches require analyzing the characteristics of the time series and this operation is usually empirical, thus lacking explicit mathematical models. For example, an important step in EWT is to segment the spectrum into several parts (Gilles, 2013). This is an empirical process and the procedure relies on the characteristics of particular time series data of interest. More explicitly, the number and position of local maxima in the spectrum determine how the partitioning process works. Another example is the SSA. The grouping operation is generally based on statistical tests or visual inspections over the components obtained in the singular value decomposition, which is controlled by the properties of the time series data as well (Hassani, 2021).

Due to the above strict constraints in addressing the boundary issue based on improving the decomposition algorithm, the algorithm-based boundary issue solutions are mainly discussed under the scenario of WT-based forecasting models. As mentioned earlier, the essential idea of WT is convolving the original time series or component time series at each level with the corresponding wavelet and scaling function decided by the selected wavelet basis. Hence, one way to address the boundary issue is to use a wavelet basis that does not involve future data, and combines it with an undecimated wavelet transform algorithm. The reason to select a wavelet basis that does not involve future data is to ensure the decomposed components are calculated only based on the data obtained previously in time. The decimated wavelet transform resembles the DWT and usually contains two phases: (i) calculating detail and approximation coefficients with high-pass and low-pass filters and (ii) decimating the obtained component time series, i.e., keeping one data sample out of every two. The purpose of decimation is to save storage space. Nevertheless, decimation causes difficulty to relate information at a given time point with different time resolutions. More explicitly, a time point at decomposition level k usually contains information of 2^k time points from the original time series, which causes significant difficulty to eliminate the future data involved. As a result, the undecimated wavelet transform is recommended for use.

Several publications have addressed the boundary issue by exploiting this idea. A representative example is the redundant Haar wavelet transform based on AT (Renaud et al., 2005; Nguyen and Nabney, 2010; Murtagh et al., 2004). Additionally, Matsusue et al. combined MODWT with the Haar wavelet to eliminate the misuse of future data. Although the Haar wavelet is the only known wavelet basis that computes the decomposed components based only on the data obtained previously in time, Luan (2005) presented an approach to generate a boundary-issue-free wavelet basis based on the existing wavelet basis. In this study, a B_3 spline wavelet transform based on AT is proposed. Although the B_3 spline wavelet requires both previous and future data points to calculate the decomposed components, the shifting operation is applied on the B_3 spline wavelet to ensure that only the known data ($\leq t$) is used to decompose data sample at time t.

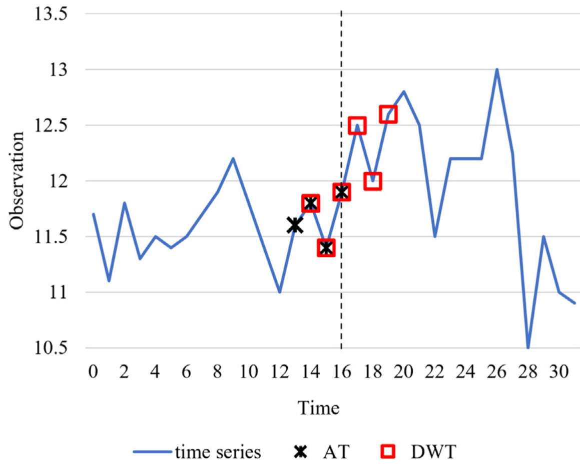

Fig. 6. Visualization of DWT and AT's future data engagement condition (Quilty and Adamowski, 2018).

Another approach to deal with the boundary issue is to utilize a wavelet transform algorithm, which calculates the decomposed components only based on the known data, called AT (Shensa et al., 1992). Fig. 6 presents an example to visualize the difference of future data engagement condition between AT and DWT, where the length of filters $L = 4$, the number of samples $N = 32$, current time index $t = 16$ and decomposition level $J = 1$. Based on this idea, a number of studies have successfully resolved the boundary issue (Adamowski and Chan, 2011; Adamowski et al., 2012; Jin and Kim, 2015; Maheswaran and Khosa, 2012a). From Fig. 6, AT does not involve future data in the decomposition process. Moreover, Quilty and Adamowski (2018) proposed a novel forecasting framework to handle the boundary issue considering the boundary effect. In addition to the aforementioned AT, a decomposition level selection strategy and a boundary correction method are combined to address the boundary effect. The boundary effect in WT is caused by the incomplete convolution at both ends of the time series (Fang et al., 2019). Hence, the coefficients affected by the boundary effect are removed to ensure the quality of decomposition. Several researchers have managed to avoid both boundary issue and boundary effect with the help of this framework (Zhou et al., 2020; Xu et al., 2021).

The aforementioned two approaches are suitable for both multi-component approach and direct approach architectures. Quilty and Adamowski (2018) proposed another approach based on MODWT, which only works for the direct approach structure. MODWT is also a wavelet transform that computes the sub-series based on known data. However, it is not an additive wavelet decomposition like AT but an energy-based wavelet transform. This introduces extra difficulties on its reconstruction, making it inapplicable to the multi-component approach structure (Quilty and Adamowski, 2018, 2021). Several studies have been reported to address the boundary issue based on MODWT (Quilty and Adamowski, 2018, 2021; Jiang et al., 2021; Barzegar et al., 2021; Mouatadid et al., 2019; Rahman et al., 2020; Ghaemi et al., 2019; Rezaali et al., 2021). The aforementioned decomposition level selection strategy and boundary correction method have also been proven effective for the boundary issue solution based on MODWT (Quilty and Adamowski, 2018).

3.2. Sampling-strategy-based boundary issue solutions

Current studies on the algorithm-based boundary issue solutions focus predominantly on the WT-based techniques, while the sampling-strategy-based solutions have the ability to solve the boundary issue in most of the decomposition methods. The rolling mechanism explained in Section 2.3 is a typical example of this type of solution. Recall that the traditional decomposition-based time series forecasting models prefer to decompose the entire dataset at the same time and then split the sub-series into training and test datasets. This makes the decomposition procedure of the training dataset use some information belonging to the test dataset. Hence, researchers have proposed a novel sampling strategy based on the rolling mechanism. The entire time series is first divided into training and test datasets. Then the training dataset is disaggregated into sub-series and used to train the forecasting models. During the test phase, the test data sample is incrementally appended to the training dataset and the decomposition is re-conducted every time a new test data sample is added (Xiao et al., 2021; Yu et al., 2021; Zuo et al., 2020). Some studies have combined the rolling-mechanism-based solution with Kalman filter and proved the efficiency of the resulting hybrid model (Maheswaran and Khosa, 2012b; Zhang et al., 2021). Kalman filter is an online forecasting model sequentially accepting the observation and updating internal states every time a new observation arrives. Hence, no target data is required in the training process. However, as the entire training dataset is decomposed together, future data leakage still exists in the training process. Therefore, the boundary issue is not completely addressed.

A straightforward solution is applying the rolling mechanism on the entire time series including both training and test datasets. However, new issues arise. The decomposition level is usually based on the complexity of the time series. As the length of the time series grows, the suitable decomposition level also changes. In the rolling-mechanism-based solution, the size of the training data is usually several times of that of test data. Hence, the decomposition level can be kept consistent. However, if the rolling mechanism is applied to the entire time series, it is hard for the decomposition level to be kept consistent during the entire decomposition process. Moreover, if the rolling mechanism is employed on the training dataset, it is impossible to obtain the decomposed target time series during the training phase. As a result, this solution is only feasible for the direct approach or hybrid models based on online learning forecasting models like Kalman filter.

To address the aforementioned decomposition level problem and target decomposition problem, several novel approaches have been reported in the literature. Fang et al. (2019) proposed an improved rolling-mechanism-based approach, i.e., stepwise-decomposition-based sampling technique. Assume S is time series data with a length of N, and M past observations are used to forecast the next data point. Table 2 and Fig. 7 illustrate the working principle of the stepwise-decomposition-based sampling technique. The decomposition is performed in a stepwise fashion over both training and test datasets. Moreover, target sub-series are obtained via decomposing the entire time series. This solves the problem of obtaining the decomposed target time series. Another sampling-strategy-based approach has also been reported in the boundary issue literature, which is based on the sliding window mechanism. The sliding window mechanism addresses the inconsistent decomposition level issue by sliding a fixed-size window over the original time series and only decomposing the time series data within the window. In other words, every time a new data sample is appended, the oldest data sample in the window is removed. In this way, the size of decomposed time series is kept constant; hence, the suitable decomposition level maintains consistent. Moreover, the target sub-series is obtained by decomposing a larger window composed of the sliding window and target time series (Kim and Valdés, 2003). Table 3 and Fig. 8 present an example of the sliding-window-based sampling strategy. Similar ideas are employed in a few

Table 2
Working principles of the stepwise-decomposition-based sampling technique.

Dataset partition	Sample ID	Explanatory data	Target data
Training dataset	Sample 1	Decompose $\{S_1, \ldots, S_M\}$	Decompose the overall time series $\{S_1, \ldots, S_N\}$
	...	...	
	Sample P	Decompose $\{S_1, \ldots, S_{M+P-1}\}$	
Test dataset	Sample P+1	Decompose $\{S_1, \ldots, S_{M+P}\}$	
	...	...	
	Sample N-M	Decompose $\{S_1, \ldots, S_{N-1}\}$	

Table 3
Working principles of the sliding-window-based sampling technique.

Dataset partition	Sample ID	Explanatory data	Target data
Training dataset	Sample 1	Decompose $\{S_1, \ldots, S_M\}$	Decompose $\{S_1, \ldots, S_{M+1}\}$
	...	...	...
	Sample P	Decompose $\{S_P, \ldots, S_{M+P-1}\}$	Decompose $\{S_P, \ldots, S_{M+P}\}$
Test dataset	Sample P+1	Decompose $\{S_{P+1}, \ldots, S_{M+P}\}$	Decompose $\{S_{P+1}, \ldots, S_{M+P+1}\}$
	...	...	...
	Sample N-M	Decompose $\{S_{N-M}, \ldots, S_{N-1}\}$	Decompose $\{S_{N-M}, \ldots, S_N\}$

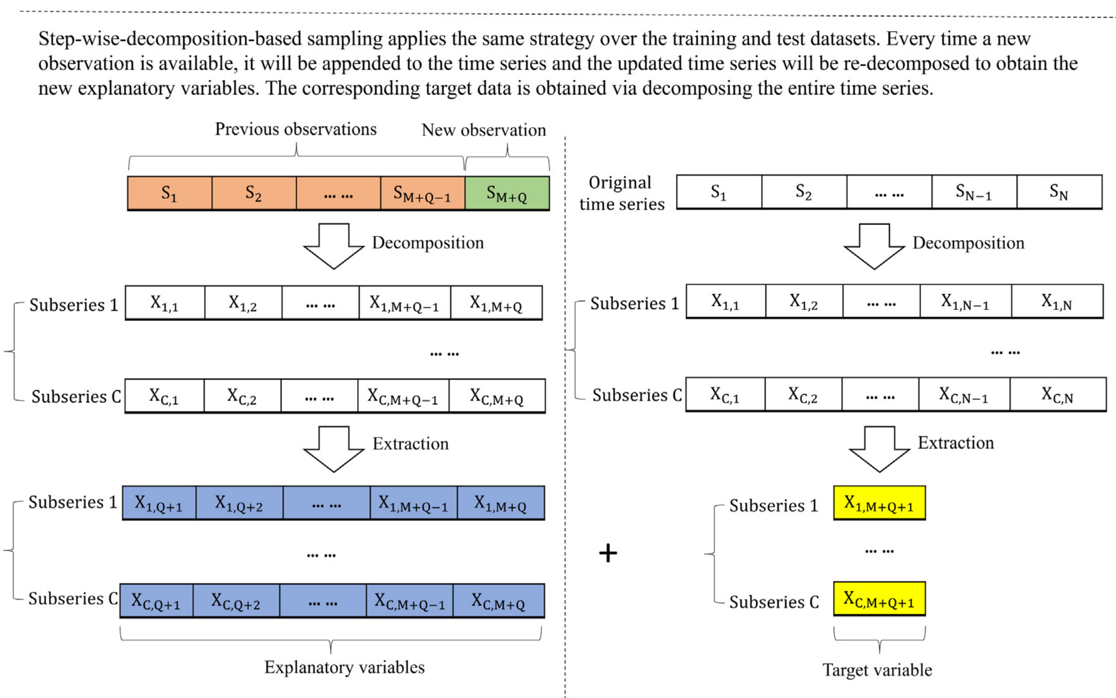

Fig. 7. Actual practices of the stepwise-decomposition-based sampling technique.

other studies (Hasumi and Kajita, 2018; Wang and Wu, 2016). Moreover, Gao et al. (2021) proposed a hybrid model based on the sliding-window-based sampling strategy, which employed the direct approach to avoid decomposing the target time series data.

3.3. Iteration-based boundary issue solutions

Yu et al. (2001) presented a novel boundary issue solution based on iteration and convergence as mentioned at the beginning of Section 3. The main procedure of this approach is listed below.

1. Initially perform time series forecasting on the original time series $\{x_{o,1}, \ldots, x_{o,n}\}$ and obtain the predicted value $\{\hat{x}_{p_1,n+1}, \ldots, \hat{x}_{p_1,n+m}\}$.
2. Disaggregate the time series with the predicted value $\{x_{o,1}, \ldots, x_{o,n}, \hat{x}_{p_{i-1},n+1}, \ldots, \hat{x}_{p_{i-1},n+m}\}$ and obtain the k sub-series $\{x^1_{o,1}, \ldots, x^1_{o,n}, \hat{x}^1_{p_{i-1},n+1}, \ldots, \hat{x}^1_{p_{i-1},n+m}\}, \ldots, \{x^k_{o,1}, \ldots, x^k_{o,n}, \hat{x}^k_{p_{i-1},n+1}, \ldots, \hat{x}^k_{p_{i-1},n+m}\}$.
3. Forecast each sub-series $\{x^1_{o,1}, \ldots, x^1_{o,n}\}, \ldots, \{x^k_{o,1}, \ldots, x^k_{o,n}\}$ and obtain the predicted values $\{\hat{x}^1_{p_i,n+1}, \ldots, \hat{x}^1_{p_i,n+m}\}, \ldots, \{\hat{x}^k_{p_i,n+1}, \ldots, \hat{x}^k_{p_i,n+m}\}$.
4. Sum the predicted sub-target-values $\{\hat{x}^1_{p_i,n+1}, \ldots, \hat{x}^1_{p_i,n+m}\}, \ldots, \{\hat{x}^k_{p_i,n+1}, \ldots, \hat{x}^k_{p_i,n+m}\}$ to yield the overall prediction $\{\hat{x}_{p_i,n+1}, \ldots, \hat{x}_{p_i,n+m}\}$.
5. Repeat Steps 2 to 4 until the converging condition is satisfied.
6. Output the prediction.

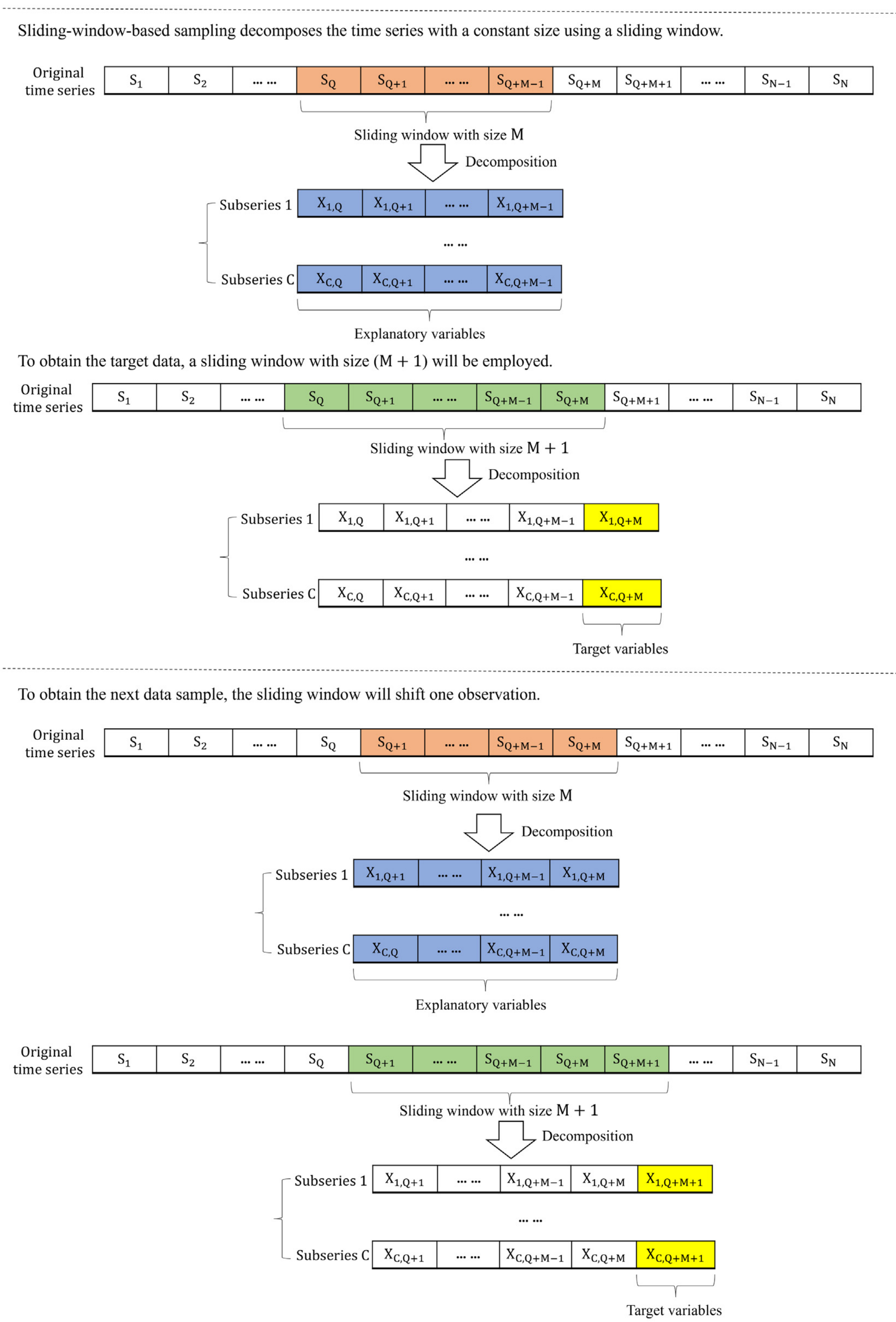

Fig. 8. Actual practices of the sliding-window-based sampling technique.

Fig. 9 is the flowchart describing the procedure of this iterative approach. However, there is no theoretical proof of whether or why convergence is guaranteed. Moreover, this approach is only verified over two denoised time series datasets using autoregressive models. Its applicability to complicated nonlinear models and non-stationary wind power time series requires substantial further investigations.

4. Discussions

4.1. Comparative discussions on different boundary issue solutions

Table 4 comprehensively depicts the advantages and disadvantages of the aforementioned boundary issue solutions. According to the comparison, the AT-based approach offers the most

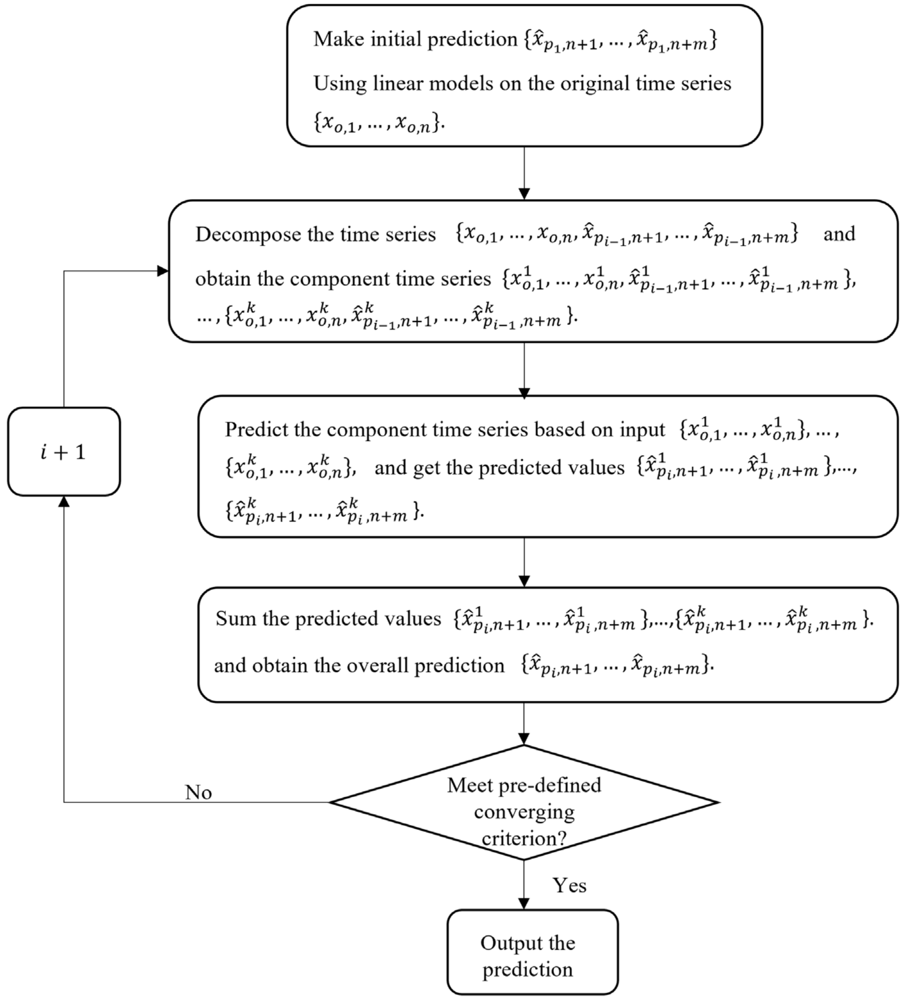

Fig. 9. Iteration-based approach (Yu et al., 2001).

complete boundary issue solution in the current literature. It overcomes all the boundary issue problems, including future data leakage, incorrect partition of training and test datasets, improper decomposition level selection and unrealistic boundary effect. The boundary correction mechanism can be combined to handle the boundary effect. Additionally, the MODWT-based method is another good choice if the direct approach is applied. However, these algorithm-based solutions can only be implemented when WT is employed as the decomposition technique.

When other decomposition methods are used for time series predictions, sampling-strategy-based solutions are a favorable choice. While the rolling-mechanism-based approach only addresses the boundary issue in the test phase, stepwise-decomposition-based and sliding-window-based approaches are more suitable to address the boundary issue. However, they both suffer from a significant limitation, i.e., the explanatory data and target data need to be decomposed separately unless the direct approach or online learning methods are employed. The purpose of this operation is to ensure the information of target data is not utilized in the decomposition of explanatory data, in order to avoid future data leakage. However, the stationarity of the component time series composed of decomposed explanatory data and target data can be worse than that of the original time series without decomposition. To avoid this problem, the direct approach or online learning methods, such as the Kalman filter, can be used.

The iteration-based approach is a solution that still requires substantial further investigations. Two studies in the literature exploit this approach. Yu et al. (2001) examined the aforementioned approach over two smooth time series, while Bašta (2014) listed it as a potential solution for solving the boundary issue. Nevertheless, there is insufficient theory to support why or even whether the convergence would eventually happen.

As mentioned before, hybrid decomposition approaches are frequently reported in the literature for decomposition-based wind power forecasting (Xiang et al., 2020; Mi et al., 2019; Li et al., 2022a). Sampling-strategy-based and iteration-based solutions are not be affected by combining the decomposition methods sequentially or parallelly. This reason is that the sampling process happens in the pre-processing phase, immediately before decomposition. Moreover, the algorithm-based solutions are also effective if the decomposition approaches employed belong to the WT family.

4.2. Potential directions for future research

Due to its highly intermittent and stochastic nature, wind power forecasting requires substantial new research effort. While decomposition-based forecasting models have shown promising results, they are susceptible to the boundary issue. As such, several directions for future investigations are presented as follows:

1. *Embed AT and MODWT into the decomposition-based hybrid models:* In the WT-based wind power forecasting models, WT, EWT and WPD are generally used for decomposition. Using AT or MODWT instead can directly solve the

Table 4
Comparisons among different boundary issue solutions.

Classification	Solution	Advantages	Disadvantages
Algorithm-based solution	Wavelet-basis-based approach	1. Work for both direct approach and multi-component approach structures. 2. The algorithm is only required to be undecimated while other algorithm-based solutions require specific algorithms. 3. The entire time series is decomposed, which saves the computation resource.	1. Only work for WT-based models. 2. The limited wavelet basis choices may cause this approach to be not suitable to handle some specific time series.
	AT-based approach	1. Work for both direct approach and multi-component approach structures. 2. No specific requirements on the wavelet basis. 3. The entire time series is decomposed altogether, which saves the computation resource.	1. Only work for WT-based models.
	MODWT-based approach	1. No specific requirements on the wavelet basis. 2. The entire time series is decomposed altogether, which saves the computation resource.	1. Only work for WT-based direct approach models.
Sampling-strategy-based solution	Rolling-mechanism-based approach	1. Work for most of the decomposition techniques. 2. Work for both direct approach and multi-component approach structures. 3. No target decomposition problem in the training phase.	1. Cost a large amount of computation resource. 2. The decomposition level may be inconsistent over the decomposition process. 3. The future data leakage problem still exists in the training phase.
	Stepwise-decomposition-based approach	1. The future data leakage problem is completely addressed. 2. Work for most of the decomposition techniques and both structures.	1. Cost a large amount of computation resources. 2. The decomposition level is inconsistent over the decomposition process. 3. The treatment of the target decomposition problem may break the stationarity of sub-series.
	Sliding-window-based approach	1. Work for most of the decomposition techniques and both structures. 2. The decomposition level is consistent over the decomposition process.	1. Cost a large amount of computation resource. 2. The treatment of the target decomposition problem may break the stationarity of sub-series.
Iteration-based solution	Iteration-based approach	1. Work for most of the decomposition techniques. 2. No need to decompose the target data.	1. Only work for the multi-component approach structure. 2. Have the highest computational cost. 3. Substantial further investigations are required to examine the feasibility of this solution.

boundary issue. Hence, it is worth exploring the AT or MODWT-based wind power forecasting models.

2. *Integrate stepwise-decomposition-based or rolling-window-based sampling strategy with existing hybrid models:* Sampling-strategy-based boundary issue solutions can be implemented to handle the boundary issue of most of the existing hybrid wind power forecasting models. Although the rolling-mechanism-based approach has already been incorporated into several decomposition-based wind power forecasting models (Yu et al., 2022; Duan et al., 2022; Deng et al., 2020), this approach has only partially, not completely, considered and resolved the boundary issue. For a better treatment of the boundary issue, it is imperative to develop the boundary-issue-eliminated hybrid models based on stepwise-decomposition-based or rolling-window-based sampling strategy.
3. *Develop boundary-issue-free hybrid models based on direct approach:* According to our review, the direct approach is rarely reported in the literature. Nevertheless, the direct approach can be incorporated with a wide range of boundary issue solutions and resolve their limitations, which include the target decomposition problem in sampling-strategy-based boundary issue solution and the reconstruction issue in the MODWT-based solution. Hence, it is possible and advantageous to develop boundary-issue-free hybrid models based on the direct approach.

5. Conclusions

In this paper, we have presented a systematic review of recently reported decomposition-based models for wind power forecasting. We have particularly focused on the ubiquitous yet unresolved boundary issue, and have surveyed their existing solutions. The decomposition-based hybrid models have been categorized based on the structures into direct approach and multi-component approach. The corresponding decomposition methods have been classified into WT-based decomposition, EMD-based decomposition, VMD, SSA and hybrid decomposition. The advantages and limitations of the hybrid models with different structures and decomposition techniques have been evaluated. Their differences in handling the boundary issue have also been discussed. Furthermore, a comprehensive review of the existing boundary issue solutions, which cover the wavelet-basis-based solution, AT-based solution, MODWT-based solution, rolling-mechanism-based solution, stepwise-decomposition-based solution, sliding-window-based solution and iteration-based solution, has been provided. To this end, the advantages, disadvantages and applicability of these approaches have been presented in detail. It is expected that our comparative discussions are useful for power engineering researchers to discover the existence of the boundary issue in their approaches and determine which solution is the most suitable for tackling their problems. Our critical review is particularly beneficial to avoid producing realistically unachievable prediction results when using decomposition-based prediction models. Our findings offer insightful and wide applicability to power system reserve scheduling research for achieving reliable integration of renewable energy sources.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: S. M. Muyeen reports article publishing charges was provided by Qatar National Library.

Data availability

No data was used for the research described in the article.

Acknowledgment

The publication of this article was funded by Qatar National Library.

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