

An Amplitude–Phase Parametric Method for Evaluating the Evolution of Fluctuation in Integrated Load-Photovoltaic-Wind Waveforms

Jule Zhao, Gang Mu, Gangui Yan, and Xiaoping Zhang

Abstract—In high-penetration renewable power systems, wind power, photovoltaic power, and most loads are non-dispatchable, and are collectively referred to as passive power. The growth of passive power increases the system demand for regulation capacity while displacing conventional regulation resources, thereby intensifying the supply–demand mismatch. Since load, photovoltaic, and wind power waveforms have distinct morphologies, their integrated waveform evolves during aggregation. Characterizing the integration properties of all passive power waveforms is therefore essential for configuring regulation resources on demand and achieving power balance. Conventional studies on source–load power characteristics mainly focus on the stochasticity of power values, while the temporal characteristics of power and the morphological evolution of integrated waveforms have received limited attention. This paper proposes an amplitude–phase analysis method for power waveforms, in which waveform morphology is characterized by amplitude and phase across multiple timescales. On this basis, the phase and amplitude relationships among multiple power waveforms are analyzed, along with the multiscale formation mechanism governing multivariate waveform integration evolution. The regular evolution trends of integrated load–wind–photovoltaic waveforms under different penetration levels are further revealed. The effectiveness of the proposed method is validated using real-world data.

Index Terms—Amplitude–phase features, high-penetration renewable energy, multi-timescale, passive power, waveform integration evolution.

I. INTRODUCTION

BUILDING a new power system with renewable energy as the mainstay is China’s fundamental pathway to achieving carbon peaking before 2030 and carbon neutrality before 2060 [1], [2]. By the end of 2024, China’s combined installed

wind and solar PV capacity had exceeded 1400 GW, already surpassing its 2030 target of 1200 GW, and the IEA projects that China’s renewable power capacity will increase by nearly 2660 GW between 2025 and 2030, with solar PV accounting for approximately 80% of this growth [3]. Therefore, future power systems will inevitably feature high renewable energy penetration [4].

Since wind and photovoltaic power are affected by natural factors, they exhibit strong uncertainty. Their large-scale integration increases system regulation demand. Meanwhile, the declining share of conventional thermal units leads to insufficient system regulation capability. The pronounced mismatch between regulation capability supply and demand in power systems may result in the coexistence of power curtailment and power shortages.

In response to the operational risks introduced by renewable power uncertainty, most studies have focused on quantitatively evaluating the uncertainty of renewable generation. Reference [5] characterizes the stochasticity and diurnal characteristics of wind power using probability. References [6], [7] predict the probabilistic characteristics of wind and photovoltaic power using deep learning and neural network methods. Reference [8] represents power uncertainty in power systems using intervals in optimal power flow analysis. For the aggregate output characteristics of multidimensional uncertain power, reference [9] uses a vine Copula method to characterize the correlations among multiple wind power outputs and develop a probabilistic model for aggregated wind power. References [10], [11] incorporate the spatiotemporal correlations between wind and photovoltaic power in uncertainty modeling. These studies mainly evaluate the uncertainty of source and load power values using statistical methods such as probability and intervals, and have been widely applied in engineering practice, including improving power system security and economy and reducing intraday unit commitment operating costs.

Real-time power balance essentially depends on the temporal fluctuation morphology of power waveforms. Reference [12] characterizes the intermittency of temporal fluctuations in wind and photovoltaic power. References [13], [14] use

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Markov chain models to describe the temporal state transition characteristics of waveforms. References [15], [16], [17] generate typical daily scenarios through time-series clustering to characterize temporal power characteristics. These studies have been widely applied in stochastic production simulation of power systems and can effectively promote renewable energy accommodation.

From the perspective of power regulation attributes in power systems, most load, wind power, and photovoltaic power are non-dispatchable, and are defined as passive power. Conventional thermal units, energy storage, and demand response are classified as active power. Different types of passive power waveforms in the system have distinct morphologies, and their morphology evolves after temporal integration. Characterizing the morphology of the integrated system power waveform is key to providing active power on demand and ensuring system power balance.

Regarding the evaluation of overall temporal fluctuations of multiple power outputs in power systems, reference [18] quantifies the complementarity among wind generation, solar generation, and load demand, reducing net-load fluctuation instability and peak–valley differences. Reference [19] analyzes the complementarity among load, photovoltaic power, and wind power, thereby reducing the regulation burden on conventional units in day-ahead scheduling and improving overall system flexibility. Studies on such complementarity have achieved favorable performance in energy storage applications for smoothing wind–solar fluctuations [20], [21].

In recent years, the integration of signal decomposition and deep learning has further advanced renewable-energy fluctuation analysis and waveform characterization. Models based on discrete wavelet transform can separate trend, periodic, and high-frequency components and, when coupled with Transformers, extract multiscale spatiotemporal features from photovoltaic or wind-power series [22], [23]. Multivariate variational mode decomposition enables the synchronous decomposition of wind-power signals, thereby preserving the consistent correspondence among modal frequencies [24]. For photovoltaic signals, ensemble empirical mode decomposition combined with variational mode decomposition can improve the modeling of residual and low-frequency components [25], while long-timescale clustering, short-timescale phase-space reconstruction, and multiscale weather classification can extract fluctuation features relevant to forecasting [26], [27]. In fluctuation smoothing and energy-storage power allocation, successive variational mode decomposition, Kalman-filter-assisted empirical mode decomposition, and area-equilibrium empirical mode decomposition have been employed for modal partitioning, frequency-band allocation, and energy-balanced control, respectively [28], [29], [30]. These studies demonstrate the effectiveness of multiscale signal processing in denoising and forecasting renewable-energy waveforms. However, their primary objectives are generally to obtain predictable modal components or improve model accuracy. They have not directly addressed how the overall fluctuation mor-

phology formed after the integration of multiple power waveforms can be interpretably parameterized by the characteristics of its constituent components.

Regarding mechanism-oriented studies on the fluctuation characteristics of integrated multiple power time series, reference [31] applied set-pair analysis to investigate the smoothing characteristics of wind-farm clusters under different numbers of wind farms, wind-speed conditions, and seasonal conditions. References [32], [33], [34] revealed the trend regularities of field-cluster power fluctuations after the aggregation of multiple renewable-energy power waveforms using time–frequency analysis methods, including autoregressive-model-based spectral analysis, variational mode decomposition, and Fourier transform. These regularities have been shown to improve wind–photovoltaic forecasting accuracy [35], [36], [37] and reduce operating costs in power-grid optimal dispatch [38], [39]. Reference [40] studied the influence of the spatial distribution characteristics of wind power on the morphology of regional integrated power curves. References [41] and [42] analyzed the characteristics of single-wind-farm power waveforms and their influence mechanisms on the evolution of fluctuation amplitudes in integrated wind-farm-cluster power. These studies mainly focus on characterizing the temporal features of medium- and long-term power waveforms and revealing the mechanisms of their integration. Their characterization depends on the regular features exhibited by stochastic waveforms over medium- and long-term timescales. Reference [43] proposed an amplitude–sequence decoupling analysis method, but its focus is on evaluating the overall fluctuation characteristics of integrated multivariate power waveforms at the daily timescale.

For power-system operation, however, dispatch decisions rely on the multiscale fluctuation morphology of all integrated passive power waveforms at daily and intraday timescales. Different types of power, such as load, photovoltaic power, and wind power, exhibit different degrees of stochasticity. Whether stable regular morphologies still exist after their large-scale integration, and how the multi-timescale morphological characteristics of the integrated waveform can be characterized by the features of element waveforms, are the key issues addressed in this paper. Therefore, it is urgent to establish a multiscale power-waveform analysis method to reveal and evaluate the multiscale formation mechanism and morphology of waveform evolution after multivariate integration.

In view of the above issues, the contributions of this paper are summarized as follows.

(1) Starting from the characteristic evaluation of short-term discrete waveforms, this paper proposes a multiscale amplitude–phase parametric method for power waveforms. The method characterizes the fluctuation intensity and fluctuation-direction morphology of power waveforms from the perspectives of amplitude and phase, respectively, and enables the “evolution” and “non-evolution” relationships of integrated waveform morphology to be analyzed through the phase characteristics among multiple waveforms.

(2) By analyzing the effects of phase differences and ampli-

tude differences among multiple power waveforms on the morphology of the integrated waveform, this paper reveals the multiscale evolution mechanism of integrated power waveforms of different types, thereby enabling the evaluation of integrated power fluctuation characteristics from the fluctuation features of element power waveforms.

(3) Based on the analysis of multivariate phase-coupling characteristics among single-type waveforms, this paper reveals the respective integrated morphological characteristics of multiple load, photovoltaic, and wind-power waveforms.

(4) The regular trends in the fluctuation characteristics of load, photovoltaic, and wind power waveforms with increasing renewable energy penetration are analyzed, enabling accurate characterization of integrated power waveform features.

II. VECTOR REPRESENTATION AND MULTI-TIMESCALE AMPLITUDE-PHASE PARAMETRIC MODELING OF POWER WAVEFORMS

A. Vector Representation of Power Waveforms

For studies on power balance in power system operation, daily power waveforms are usually considered, and power waveforms obtained from data acquisition systems are typically discrete. Without loss of generality, a passive power waveform $\mathbf{P}_a$ is represented by a v -dimensional row vector as

$$\mathbf{P}_a = [P_{a,1}, P_{a,2}, \dots, P_{a,v}] \quad (1)$$

where the waveform sampling rate is ξ points/h, and thus $v = 24\xi$.

Fluctuations in passive power waveforms in power systems create regulation capability demand. Characterizing the fluctuation morphology of passive power is therefore a fundamental way to understand system regulation capability demand. To describe power waveform fluctuations more directly, the power waveform vector $\mathbf{P}_a$ is decomposed into a mean vector $\bar{\mathbf{P}}_a$ and a fluctuation vector $\tilde{\mathbf{P}}_a$. The mean of the waveform vector $\mathbf{P}_a$ is defined as

$$\bar{\mathbf{P}}_a = \frac{1}{v} \sum_{q=1}^v P_{a,q} \quad (2)$$

Thus, the “mean + fluctuation” representation of the power waveform is

$$\mathbf{P}_a = \bar{\mathbf{P}}_a + \tilde{\mathbf{P}}_a \quad (3)$$

where

$$\begin{cases} \bar{\mathbf{P}}_a = [1, 1, \dots, 1] \bar{P}_a \\ \tilde{\mathbf{P}}_a = [\tilde{P}_{a,1}, \tilde{P}_{a,2}, \dots, \tilde{P}_{a,v}] \end{cases} \quad (4)$$

Clearly, the mean vector $\bar{\mathbf{P}}_a$ is a constant vector, whereas the fluctuation vector $\tilde{\mathbf{P}}_a$ has zero mean.

To measure the morphology of the fluctuation vector $\tilde{\mathbf{P}}_a$, a

zero-mean v -dimensional monotonically increasing vector is defined as the daily monotonic waveform $\mathbf{P}_m$, which serves as the reference for $\tilde{\mathbf{P}}_a$

$$\mathbf{P}_m = [P_{m,1}, P_{m,2}, \dots, P_{m,v}] \quad (5)$$

where the system base power P_{base} (in MW) is selected as the maximum amplitude of $\mathbf{P}_m$. The q^{th} element of $\mathbf{P}_m$, $q = 1, 2, \dots, v$, is given by

$$P_{m,q} = -P_{\text{base}} + (q-1) \frac{P_{\text{base}}}{v-1} \quad (6)$$

B. Multi-Timescale Amplitude-Phase Representation of Waveform Vectors

For complex passive power waveforms with strong stochasticity, parameterizing only their full-period trend features ignores fluctuations at shorter time scales and cannot accurately characterize the overall waveform morphology. To accurately characterize the integrated morphology of multiple power waveforms, a multi-timescale parametric analysis method for power waveforms should be developed to analyze multivariate waveform integration from a multi-timescale perspective.

To obtain the multi-timescale parametric representation of waveform $\tilde{\mathbf{P}}_a$, the multi-timescale decomposition of the monotonic waveform $\mathbf{P}_m$ is first studied.

For the v -dimensional daily monotonic waveform $\mathbf{P}_m$, the maximum number of bisections J is defined as

$$J = \max_j \{v = 2^j \alpha_{\text{odd}}\} \quad (7)$$

where α_{odd} is an odd number. For example, $J = 5$ when $v = 96$, and $J = 3$ when $v = 24$.

After the j^{th} bisection of the daily monotonic waveform vector $\mathbf{P}_m$, it is divided into $2s_j$ sub-vectors, each containing r_j elements. Thus, $r_j = v/(2s_j)$ and $s_j = 2^{j-1}$.

The unit vector for the j^{th} bisection of the daily monotonic waveform vector $\mathbf{P}_m$ is defined as

$$\mathbf{I}_m^j = \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix}_{1 \times r_j} \quad (8)$$

The base-wave group vector for the j^{th} bisection is defined as

$$\mathbf{I}_{m,\text{base},i}^j = \begin{bmatrix} -\mathbf{I}_m^j & \mathbf{I}_m^j \end{bmatrix}_{1 \times 2r_j} \quad (9)$$

For the first bisection of the daily monotonic waveform vector $\mathbf{P}_m$, the means of the two sub-vectors are calculated. The two means have equal absolute values and opposite signs. The amplitude of the monotonic waveform component after the first bisection is denoted by $P_m^1 = \tilde{P}_{\text{max}}/2$. Similarly, the amplitude of the monotonic waveform component at the j^{th} bisection scale is $P_m^j = \tilde{P}_{\text{max}}/2^{s_j}$.

Thus, the daily monotonic waveform component P_m^j at the j^{th} bisection scale can be defined as

$$\begin{cases} \mathbf{P}_m^j = \mathbf{P}_m^j \mathbf{I}_{m,\text{base}}^j \\ \mathbf{I}_{m,\text{base}}^j = [\mathbf{I}_{m,\text{base},1}^j, \mathbf{I}_{m,\text{base},2}^j, \dots, \mathbf{I}_{m,\text{base},s_j}^j] \end{cases} \quad (10)$$

Accordingly, the daily monotonic waveform vector $\mathbf{P}_m$ can be decomposed over multiple scales up to the maximum number of bisections J . In summary, $\mathbf{P}_m$ can be expressed as

$$\mathbf{P}_m = \sum_{j=1}^J \mathbf{P}_m^j + \delta \mathbf{P}_m^j \quad (11)$$

Similarly, to construct the timescale $-j$ component $\tilde{\mathbf{P}}_a^j$ of waveform $\tilde{\mathbf{P}}_a$, the waveform coefficient corresponding to the two half segments associated with the i^{th} base-wave group vector $\mathbf{I}_{m,\text{base},i}^j$ is defined as $\tilde{\mathbf{P}}_{a,i}^j$, calculated by

$$\tilde{\mathbf{P}}_{a,i}^j = \frac{1}{s_j} \sum_{q=(2i-1)s_j+1}^{q=2is_j} \tilde{\mathbf{P}}_{a,q}^j, \quad i = 1, 2, \dots, s_j \quad (12)$$

Then, the scale- j component $\tilde{\mathbf{P}}_a^j$ of waveform $\tilde{\mathbf{P}}_a$ is expressed as

$$\tilde{\mathbf{P}}_a^j = [\tilde{\mathbf{P}}_{a,1}^j \mathbf{I}_{m,\text{base},1}^j, \dots, \tilde{\mathbf{P}}_{a,i}^j \mathbf{I}_{m,\text{base},i}^j, \dots, \tilde{\mathbf{P}}_{a,s_j}^j \mathbf{I}_{m,\text{base},s_j}^j] \quad (13)$$

The waveform coefficient $\tilde{\mathbf{P}}_{a,i}^j$ of the i^{th} square wave in $\tilde{\mathbf{P}}_a^j$ contains both the amplitude and phase characteristics of this square wave. The magnitude of $|\tilde{\mathbf{P}}_{a,i}^j|$ represents the amplitude of the waveform coefficient $\tilde{\mathbf{P}}_{a,i}^j$, while the sign of $\tilde{\mathbf{P}}_{a,i}^j$ relative to the amplitude $\mathbf{P}_m^j$ of the monotonic waveform component $\mathbf{P}_m^j$ represents its phase, defined as $\theta_{a,i}^j$, the amplitude-phase representation of the waveform coefficient $\tilde{\mathbf{P}}_{a,i}^j$ is given by:

$$\tilde{\mathbf{P}}_{a,i}^j = |\tilde{\mathbf{P}}_{a,i}^j| \theta_{a,i}^j \quad (14)$$

Here, $\theta_{a,i}^j = 1$ when $\tilde{\mathbf{P}}_{a,i}^j$ has the same sign as $\mathbf{P}_m^j$, and $\theta_{a,i}^j = -1$ when they have opposite signs, i.e.,

$$\theta_{a,i}^j = \begin{cases} 1, & \text{if } \tilde{\mathbf{P}}_{a,i}^j \mathbf{P}_m^j > 0 \\ -1, & \text{if } \tilde{\mathbf{P}}_{a,i}^j \mathbf{P}_m^j < 0 \end{cases} \quad (15)$$

The phase $\theta_{a,i}^j$ indicates the fluctuation direction of the i^{th} square wave in the waveform component $\tilde{\mathbf{P}}_a^j$.

Substituting Eqs. (14) and (15) into Eq. (13), the further characterization of $\tilde{\mathbf{P}}_a^j$ is obtained as follows

$$\begin{aligned} \tilde{\mathbf{P}}_a^j = & \\ & [|\tilde{\mathbf{P}}_{a,1}^j| \theta_{a,1}^j \mathbf{I}_{m,\text{base},1}^j, \dots, |\tilde{\mathbf{P}}_{a,i}^j| \theta_{a,i}^j \mathbf{I}_{m,\text{base},i}^j, \dots, |\tilde{\mathbf{P}}_{a,s_j}^j| \theta_{a,s_j}^j \mathbf{I}_{m,\text{base},s_j}^j] \end{aligned} \quad (16)$$

Taking the s_j magnitudes $|\tilde{\mathbf{P}}_{a,i}^j|$ in Eq. (16) as the diagonal elements, an amplitude matrix is constructed and defined as $\mathbf{k}_{Pa}^j$, whose characterization is given as follows:

$$\mathbf{k}_{Pa}^j = \text{diag}(|\tilde{\mathbf{P}}_{a,1}^j|, |\tilde{\mathbf{P}}_{a,i}^j|, \dots, |\tilde{\mathbf{P}}_{a,s_j}^j|) \quad (17)$$

Taking the s_j phase values $\theta_{a,i}^j$ in Eq. (16) as the diagonal elements, a phase matrix is constructed and defined as $\boldsymbol{\theta}_a^j$, which is characterized by

$$\boldsymbol{\theta}_a^j = \text{diag}(\theta_{a,1}^j, \dots, \theta_{a,i}^j, \dots, \theta_{a,s_j}^j) \quad (18)$$

Thus, the amplitude-phase representation of waveform $\tilde{\mathbf{P}}_a$ at timescale j is

$$\tilde{\mathbf{P}}_a^j = \mathbf{I}_{m,\text{base}}^j \mathbf{k}_{Pa}^j \boldsymbol{\theta}_a^j \quad (19)$$

In general, the timescale $-j$ component $\tilde{\mathbf{P}}_a^j$ of waveform vector $\tilde{\mathbf{P}}_a$ is a square-wave sequence with varying amplitudes. To characterize its amplitude feature over the full period, the average amplitude of $\tilde{\mathbf{P}}_a^j$ is defined as

$$\tilde{\mathbf{P}}_{a,\text{av}}^j = \frac{1}{s_j} \sum_{i=1}^{s_j} |\tilde{\mathbf{P}}_{a,i}^j| \quad (20)$$

Thus, the average amplitude-phase vector of the timescale $-j$ component $\tilde{\mathbf{P}}_a^j$ of waveform vector $\tilde{\mathbf{P}}_a$ is

$$\begin{aligned} \tilde{\mathbf{P}}_{a,\text{av}}^j = & \tilde{\mathbf{P}}_{a,\text{av}}^j [\theta_{a,1}^j \mathbf{I}_{m,\text{base},1}^j, \dots, \theta_{a,i}^j \mathbf{I}_{m,\text{base},i}^j, \dots, \theta_{a,s_j}^j \mathbf{I}_{m,\text{base},s_j}^j] = \\ & \mathbf{I}_{m,\text{base}}^j \tilde{\mathbf{P}}_{a,\text{av}}^j \boldsymbol{\theta}_a^j \end{aligned} \quad (21)$$

Therefore, the average amplitude-phase approximate representation of $\tilde{\mathbf{P}}_a^j$ is

$$\tilde{\mathbf{P}}_a^j = \mathbf{I}_{m,\text{base}}^j \tilde{\mathbf{P}}_{a,\text{av}}^j \boldsymbol{\theta}_a^j + \delta \tilde{\mathbf{P}}_a^j = \tilde{\mathbf{P}}_a^{j,\text{av}} + \delta \tilde{\mathbf{P}}_a^j \quad (22)$$

where $\delta \tilde{\mathbf{P}}_a^j$ is the average amplitude-phase representation deviation of component waveform component $\tilde{\mathbf{P}}_a^j$.

Taking the fourth time-scale component $\tilde{\mathbf{P}}_a^4$ of a certain waveform $\tilde{\mathbf{P}}_a$ as an example, its average amplitude-phase characterization is illustrated in Fig. 1

Accordingly, the multiscale average amplitude-phase approximate representation of waveform $\tilde{\mathbf{P}}_a$ is

$$\tilde{\mathbf{P}}_a = \tilde{\mathbf{P}}_a^{\text{av}} + \delta \tilde{\mathbf{P}}_{a,\text{all}} = \sum_{j=1}^J \tilde{\mathbf{P}}_{a,\text{av}}^j \boldsymbol{\theta}_a^j + \delta \tilde{\mathbf{P}}_{a,\text{all}} \quad (23)$$

Here, $\tilde{\mathbf{P}}_a^{\text{av}}$ is the average amplitude-phase vector of $\tilde{\mathbf{P}}_a$, and $\delta \tilde{\mathbf{P}}_{a,\text{all}}$ is the multiscale average amplitude-phase representation deviation of $\tilde{\mathbf{P}}_a$.

The ratio coefficient between the average amplitude $\tilde{\mathbf{P}}_{a,\text{av}}^j$ of component $\tilde{\mathbf{P}}_a^j$ and the amplitude $\mathbf{P}_m^j$ of monotonic waveform component $\mathbf{P}_m^j$ is defined as

$$k_{a,m}^{j,\text{av}} = \frac{\tilde{\mathbf{P}}_{a,\text{av}}^j}{\mathbf{P}_m^j} \quad (24)$$

Thus, the multi-timescale average amplitude-phase representation of $\tilde{\mathbf{P}}_a$ based on the monotonic waveform $\mathbf{P}_m$ is

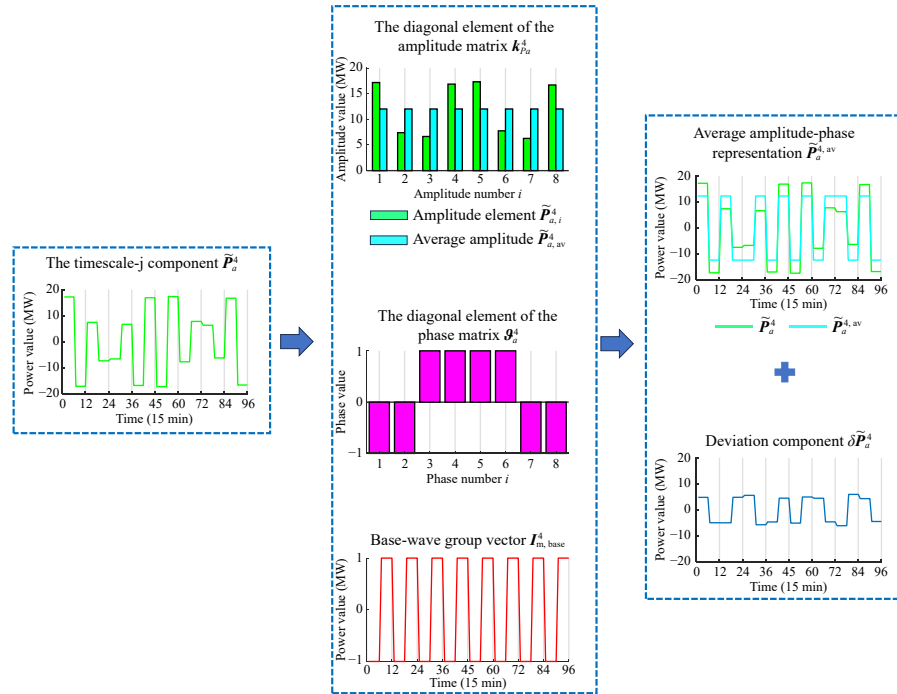


Fig. 1. The average amplitude-phase representation of $\tilde{P}_a^j$.

$$\tilde{P}_a = \sum_{j=1}^J I_{m,base}^j k_{a,m}^{j,av} P_m^j \theta_a^j + \delta \tilde{P}_{a,all} \quad (25)$$

It can be seen that, when the average amplitude-phase representation deviation is neglected, the morphology of waveform $\tilde{P}_a$ is determined by the amplitude coefficient $k_{a,m}^{j,av}$ at each timescale and the morphology of the phase waveform θ_a^j at each timescale.

Fig. 2 shows the multi-timescale average amplitude-phase parametric representation of waveform $\tilde{P}_a$ when it is a sinusoidal waveform.

The last column in Fig. 2 presents the multi-timescale average amplitude-phase vector $\tilde{P}_a^{av}$ of $\tilde{P}_a$. It can be seen that the

standard deviation intensity of the deviation $\delta \tilde{P}_{a,all}$ of the multi-timescale average amplitude-phase vector $\tilde{P}_a^{av}$ is $\sigma^2(\delta \tilde{P}_{a,all}) = 1\%$, demonstrating that the multi-timescale average amplitude-phase representation effectively characterizes power waveform morphology.

The penultimate column in Fig. 2 shows the model $\tilde{P}_{a,\theta}$, in which the amplitude coefficients $k_{a,m}$ at all timescale are set to 1 and only phase information is retained. The correlation coefficient between waveform vector $\tilde{P}_{a,\theta}$ and waveform vector $\tilde{P}_a$ is $\text{corr}(\tilde{P}_{a,\theta}, \tilde{P}_a) = 0.9$, verifying that the phase of $\tilde{P}_a$ dominates its temporal morphology.

The third column from the right in Fig. 2 shows the model $\tilde{P}_{a,k}$, in which the phases of $\tilde{P}_a$ at all timescale are set to 1 and

Time scale	$P_m^{j,av}$ (MW)	P_m	$\tilde{P}_a$	$\tilde{P}_a^{j,av}$	$k_{a,m}^{j,av}$	The diagonal element of the phase matrix θ_a^j	$\tilde{P}_{a,\theta} = \sum_{j=1}^J k_{a,m}^{j,av} P_m^j \theta_a^j$	$\tilde{P}_{a,k} = \sum_{j=1}^J P_m^j \theta_a^j$	$\tilde{P}_a^{av} = \sum_{j=1}^J k_{a,m}^{j,av} P_m^j \theta_a^j$
Full time scale	96			106.8					
							$\Delta \tilde{P}_{a,\theta} = 1.09 \Delta \tilde{P}_a$	$\text{corr}(\tilde{P}_{a,\theta}, \tilde{P}_a) = 0.9$	$\sigma^2(\delta \tilde{P}_{a,all}) = 1\%$
Time scale 1	48			61.5	1.12				
Time scale 2	24			2.3	0.08				
Time scale 3	12			25	1.84				
Time scale 4	6			12	1.76				
Time scale 5	3			6	1.78				

Fig. 2. Multi-timescale average amplitude-phase parametric representation of element waveform $\tilde{P}_a$.

only the amplitude information is retained. It can be seen that the peak–valley differences of waveform vector $\tilde{\mathbf{P}}_{a,k}$ and component waveform vector $\tilde{\mathbf{P}}_a$ satisfy $\Delta\tilde{\mathbf{P}}_{a,k} = 1.09\Delta\tilde{\mathbf{P}}_a$. This verifies that the amplitude coefficients of component waveform $\tilde{\mathbf{P}}_a$ dominate its fluctuation amplitude.

III. EVOLUTION CHARACTERISTICS OF MULTIVARIATE POWER WAVEFORM INTEGRATION

In new power systems, the fluctuation morphology of integrated multivariate passive power waveforms determines system regulation demand. It is therefore necessary to investigate the evolutionary relationship from component waveform fluctuations to the fluctuation morphology of the integrated waveform.

A. Integration of Multiple Power Waveforms and Extreme Evolution Scenarios

When n_0 power waveforms are integrated, the “mean + fluctuation” representation of the integrated waveform $\mathbf{P}_\Sigma$ is

$$\mathbf{P}_\Sigma = \bar{\mathbf{P}}_\Sigma + \tilde{\mathbf{P}}_\Sigma \quad (26)$$

The fluctuation morphology is represented only by its fluctuation component $\tilde{\mathbf{P}}_\Sigma$, which is composed of the fluctuation components $\tilde{\mathbf{P}}_a$ of the n_0 power waveforms involved in integration:

$$\tilde{\mathbf{P}}_\Sigma = \sum_{a=1}^{n_0} \tilde{\mathbf{P}}_a \quad (27)$$

For convenience, the fluctuation components $\tilde{\mathbf{P}}_\Sigma$ of the n_0 power waveforms are hereafter referred to as element waveforms, and $\tilde{\mathbf{P}}_\Sigma$ is referred to as the integrated waveform.

Consider the integrated waveform $\tilde{\mathbf{P}}_a + \tilde{\mathbf{P}}_b$ formed by two zero-mean waveforms $\tilde{\mathbf{P}}_a$ and $\tilde{\mathbf{P}}_b$. If $\tilde{\mathbf{P}}_a = \tilde{\mathbf{P}}_b$, the normalized integrated waveform has the same morphology as the component waveforms:

$$\tilde{\mathbf{P}}_{a+b}^* = \tilde{\mathbf{P}}_a^* = \tilde{\mathbf{P}}_b^* \quad (28)$$

This scenario is defined as no evolution of the integrated waveform. If the two waveforms involved in integration are reciprocal waveforms, i.e., $\tilde{\mathbf{P}}_b = -\tilde{\mathbf{P}}_a$, the integrated waveform $\tilde{\mathbf{P}}_{a+b}$ is a zero vector:

$$\tilde{\mathbf{P}}_{a+b} = \tilde{\mathbf{P}}_{a+b}^* = 0 \quad (29)$$

This scenario is defined as extreme evolution of the integrated waveform. In general, the integration of arbitrary waveforms lies between these two extreme cases.

B. Evolution Intensity of Integrated Multivariate Power Waveform Fluctuations

For n_0 element waveform vectors $\tilde{\mathbf{P}}_a (a = 1, 2, 3, \dots, n_0)$, when modeling deviations are neglected, the multiscale representation of the integrated waveform is

$$\tilde{\mathbf{P}}_\Sigma = \sum_{j=1}^J \sum_{a=1}^{n_0} \mathbf{I}_{m,\text{base}}^j P_{m,\text{base}}^j k_{a,m}^{j,\text{av}} \boldsymbol{\theta}_a^j \quad (30)$$

The i^{th} square-wave component $\tilde{\mathbf{P}}_{\Sigma,i}^j$ in the timescale- j component $\tilde{\mathbf{P}}_\Sigma^j$ of the integrated waveform is expressed as

$$\tilde{\mathbf{P}}_{\Sigma,i}^j = P_{m,\text{base}}^j \sum_{a=1}^{n_0} \mathbf{I}_{m,\text{base}}^j k_{a,m}^{j,\text{av}} \boldsymbol{\theta}_a^j \quad (31)$$

During multivariate waveform integration, the phase relationships among waveforms directly reflect their fluctuation morphology relationships.

For the n_0 component waveforms, at the i^{th} square wave of timescale j , the phase $\theta_{a,i}^j$ corresponding to $\tilde{\mathbf{P}}_{a,i}^j$ takes either 1 or -1 . The numbers of waveform components corresponding to these two cases are denoted by $n_{1,i}^j$ and $n_{2,i}^j$, respectively, with $n_{1,i}^j + n_{2,i}^j = n_0$. The component $\tilde{\mathbf{P}}_{a,i}^j$ satisfying $\theta_{a,i}^j = 1$ is defined as a positive-phase component, and its average amplitude coefficient is denoted by $k_{n_{1,i}^j}^j$. The component $\tilde{\mathbf{P}}_{a,i}^j$ satisfying $\theta_{a,i}^j = -1$ is defined as a negative-phase component, and its average amplitude coefficient is denoted by $k_{n_{2,i}^j}^j$. The average amplitude coefficient of the n_0 element waveform components is denoted by $k_{n_0,i}^j$. The coefficients $k_{n_{1,i}^j}^j$, $k_{n_{2,i}^j}^j$, and $k_{n_0,i}^j$ are expressed as follows:

$$\begin{cases} k_{n_{1,i}^j}^j = \frac{1}{n_{1,i}^j} \sum_{a=1}^{n_{1,i}^j} k_{a,m}^{j,\text{av}} \\ k_{n_{2,i}^j}^j = \frac{1}{n_{2,i}^j} \sum_{a=1}^{n_{2,i}^j} k_{a,m}^{j,\text{av}} \\ k_{n_0,i}^j = \frac{1}{n_0} \sum_{a=1}^{n_0} k_{a,m}^{j,\text{av}} \end{cases} \quad (32)$$

The deviations of $k_{n_{1,i}^j}^j$ and $k_{n_{2,i}^j}^j$ from the average amplitude coefficient $k_{n_0,i}^j$ of the n_0 element waveforms are defined as $\delta k_{n_{1,i}^j}^j$ and $\delta k_{n_{2,i}^j}^j$, respectively:

$$\begin{cases} \delta k_{n_{1,i}^j}^j = k_{n_{1,i}^j}^j - k_{n_0,i}^j \\ \delta k_{n_{2,i}^j}^j = k_{n_{2,i}^j}^j - k_{n_0,i}^j \\ \delta k_{n_{1,i}^j}^j n_{1,i}^j + \delta k_{n_{2,i}^j}^j n_{2,i}^j = 0 \end{cases} \quad (33)$$

The sum of the phases of all positive-phase component waveform components is defined as $\theta_{\Sigma,i}^{j,+}$, and the sum of the phases of all negative-phase component waveform components is defined as $\theta_{\Sigma,i}^{j,-}$, with $\theta_{\Sigma,i}^{j,+} = n_{1,i}^j$, $\theta_{\Sigma,i}^{j,-} = -n_{2,i}^j$. Thus, according to Eqs. (31)–(33), the amplitude $P_{\Sigma,i}^j$ of the i^{th} square-wave component $\tilde{\mathbf{P}}_{\Sigma,i}^j$ at timescale j of the integrated waveform $\tilde{\mathbf{P}}_\Sigma$ is expressed as follows:

$$\tilde{\mathbf{P}}_{\Sigma,i}^j = P_{m,\text{base}}^j \left| \theta_{\Sigma,i}^j k_{n_0,i}^j + n_0 \delta k_{n_{1,i}^j}^j + \theta_{\Sigma,i}^j \delta k_{n_{1,i}^j}^j \right| \quad (34)$$

where $\theta_{\Sigma,i}^j = \theta_{\Sigma,i}^{j,+} + \theta_{\Sigma,i}^{j,-}$ is the integrated phase of the n_0 element waveform components $\tilde{P}_{a,i}^j$. Its absolute value reflects the phase similarity among multiple waveforms. The term $\delta k_{n_1,i}^j$ reflects the difference between the average amplitude of positive-phase element waveform components and that of negative-phase element waveform components among the n_0 components $\tilde{P}_{a,i}^j$, hereafter referred to as the amplitude difference.

It follows from Eq. (34) that, for any interval at any timescale, the characteristics of the integrated waveform $\tilde{P}_{\Sigma}$ are determined by the integrated phase, the amplitude difference, and the coupling strength between the amplitude difference and the integrated phase among multiple waveforms.

When phase differences exist among multiple waveforms, positive and negative amplitude cancellation inevitably occurs during integration. This is defined as fluctuation evolution of the integrated waveform. When the phases $\theta_{a,i}^j$ of the i^{th} square-wave components at the j^{th} timescale of the n_0 element waveforms are all identical, the amplitude $\tilde{P}_{\Sigma,i}^j$ of the i^{th} square-wave component at the j^{th} timescale of the integrated waveform equals the sum of the amplitudes of all component waveforms at that timescale. This is defined as the result of $\tilde{P}_{\Sigma,i}^j$ under the in-phase condition of element waveforms, denoted by $\tilde{P}_{\Sigma}^{j,\text{NE}}$

$$\tilde{P}_{\Sigma,i}^j = \tilde{P}_{\Sigma}^{j,\text{NE}} = n_0 P_m^j k_{n_0,i}^j \quad (35)$$

Using $\tilde{P}_{\Sigma}^{j,\text{NE}}$ as the benchmark, the deviation of the amplitude $\tilde{P}_{\Sigma,i}^j$ of the i^{th} square-wave component at timescale j from $\tilde{P}_{\Sigma}^{j,\text{NE}}$ is defined as its evolution rate $\eta_{\Sigma,\theta,k,i}^j$

$$\eta_{\Sigma,\theta,k,i}^j = 1 - \frac{\tilde{P}_{\Sigma,i}^j}{\tilde{P}_{\Sigma}^{j,\text{NE}}} = 1 - \left| \theta_{\Sigma,i}^{j*} + \delta k_{n_1,i}^{j*} + \delta k_{n_1,i}^{j*} \theta_{\Sigma,i}^{j*} \right| \quad (36)$$

where $\theta_{\Sigma,i}^{j*}$ is the integrated phase of the n_0 element waveforms for the i^{th} square wave at timescale j , and $\delta k_{n_1,i}^{j*}$ is the amplitude-difference rate among element waveforms. Its range is $-n_2^j/n_1^j \leq \delta k_{n_1,i}^{j*} \leq n_2^j/n_1^j$. They are expressed as

$$\begin{cases} \theta_{\Sigma,i}^{j*} = \frac{\theta_{\Sigma,i}^j}{n_0} \\ \delta k_{n_1,i}^{j*} = \frac{\delta k_{n_1,i}^j}{k_{n_0,i}^j} \end{cases} \quad (37)$$

It can be seen that the amplitude evolution rate $\eta_{\Sigma,\theta,k,i}^j$ of the integrated waveform component $\tilde{P}_{\Sigma,i}^j$ is also determined by the integrated phase, amplitude-difference rate, and the coupling strength between amplitude difference and in-phase rate strength among multiple waveforms.

The phase relationships among multiple waveforms directly reflect their evolution relationships during integration. When

$\delta k_{n_1,i}^{j*} = 0$, the evolution rate is $\eta_{\Sigma,\theta,k,i}^j = 1 - \left| \theta_{\Sigma,i}^{j*} \right|$. The phase-difference rate of multiple waveforms is defined as

$$\delta \theta_{\Sigma,i}^{j*} = 1 - \left| \theta_{\Sigma,i}^{j*} \right| \quad (38)$$

The phase-difference rate $\delta \theta_{\Sigma,i}^{j*}$ reflects the intensity of phase differences among the i^{th} square waves of multiple waveforms at the j^{th} timescale.

It can be seen that, in this case, the evolution intensity of the integrated waveform is determined by the phase-difference rate $\delta \theta_{\Sigma,i}^{j*}$. When $\theta_{\Sigma,i}^{j*} = 0$, the integrated waveform does not evolve; when $\delta \theta_{\Sigma,i}^{j*} = 1$, the integrated waveform undergoes extreme evolution.

When $\delta k_{n_1,i}^{j*} = \pm 1$, $\eta_{\Sigma,\theta,k,i}^j = 0$, and no cancellation evolution occurs in the amplitude of the integrated waveform component $\tilde{P}_{\Sigma,i}^j$.

The mean evolution rate of all square-wave components at the j^{th} timescale is defined as the evolution rate $\eta_{\Sigma,\theta,k}^j$ of the integrated waveform at this timescale

$$\eta_{\Sigma,\theta,k}^j = \frac{1}{s_j} \sum_{i=1}^{s_j} \eta_{\Sigma,\theta,k,i}^j \quad (39)$$

Thus, the full-timescale evolution rate of the integrated waveform $\tilde{P}_{\Sigma}$ is

$$\eta_{\Sigma,\theta,k} = \frac{\sum_{j=1}^J \tilde{P}_{\Sigma}^{j,\text{NE}} \eta_{\Sigma,\theta,k}^j}{\sum_{j=1}^J \tilde{P}_{\Sigma}^{j,\text{NE}}} \quad (40)$$

The above analysis shows that integrated waveform evolution is fundamentally caused and dominated by phase differences among element waveforms. When the amplitude differences among multiple element waveforms are small, the evolution characteristics of the integrated waveform can be estimated using only the phase characteristics among multiple element waveforms.

At the j^{th} timescale, the evolution rate of the integrated waveform can be estimated by the average phase difference ratio $\delta \theta_{\Sigma}^{j*}$ of multiple element waveforms at this timescale

$$\eta_{\Sigma,\theta}^j = \delta \theta_{\Sigma}^{j*} = 1 - \frac{1}{s_j} \sum_{i=1}^{s_j} \left| \theta_{\Sigma,i}^{j*} \right| \quad (41)$$

The full- timescale evolution rate of the integrated waveform can be estimated by the phase difference ratio of multiple element waveforms at different scales:

$$\eta_{\Sigma,\theta} = \delta \theta_{\Sigma}^* = 1 - \frac{\sum_{j=1}^J \tilde{P}_{\Sigma}^{j,\text{NE}} \delta \theta_{\Sigma}^{j*}}{\sum_{j=1}^J \tilde{P}_{\Sigma}^{j,\text{NE}}} \quad (42)$$

C. Influence of Phase Characteristics Among Multiple Single-Type Waveforms on Their Integration Evolution

To analyze the effect of inter-waveform phase characteristics on the integration evolution of waveforms of the same type, multiple daily waveform data sampled at 15-min intervals in a certain region on the same day were used. Based on

these data, integration scenarios were constructed for 12 load waveforms, 12 photovoltaic waveforms, and 12 wind power waveforms. As shown in Fig. 3. These scenarios were used to verify the effect of inter-waveform phase differences on the evolution of the integrated waveform.

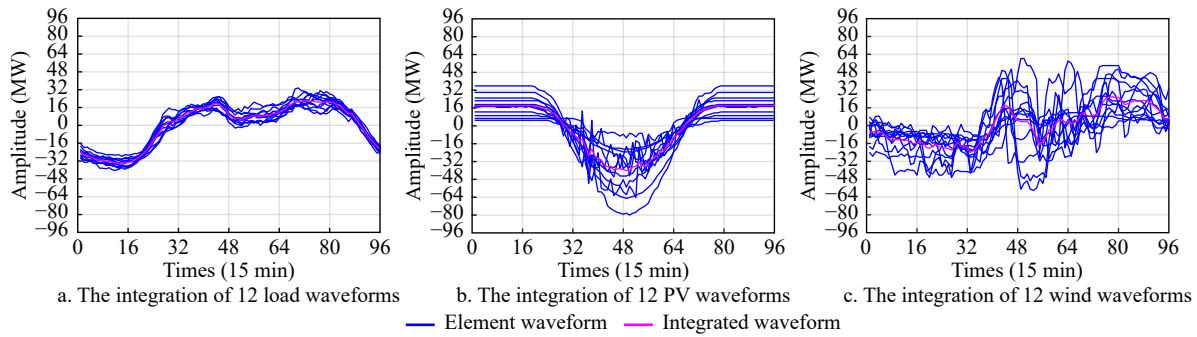


Fig. 3. Integration scenario of twelve single-type waveforms.

To further validate the effect of phase differences among multiple waveforms on the characteristics of the integrated waveform, Fig. 4 presents the evolution rates and phase-difference rates of the three types of waveforms. It can be seen that

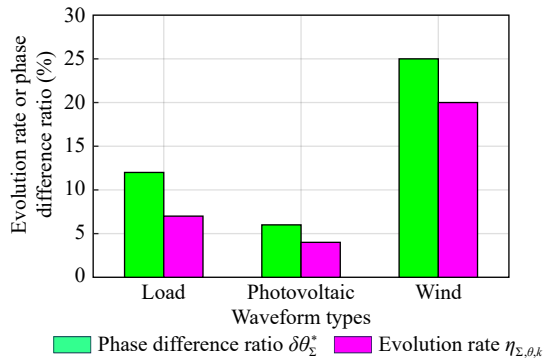


Fig. 4. Phase difference ratio and evolution intensity of integrated waveforms under different integration timescale.

the phase-difference rate is the smallest among multiple photovoltaic waveforms, followed by load waveforms, and is the largest among wind power waveforms. This explains why the evolution rate follows the pattern of wind power > load > photovoltaic power.

To further analyze the characteristics of single-type waveforms under different integration scales, the phase-difference rates and evolution rates of integrated load, photovoltaic, and wind power waveforms were calculated for integration scales of 12, 24, 36, 48, 60, and 72 waveforms, as shown in Fig. 5.

It can be seen that, as the waveform integration scale increases, the evolution rates of the integrated load and photovoltaic waveforms remain within a very small range, indicating that almost no evolution occurs. This is because the phase-difference rates among multiple load waveforms and among multiple photovoltaic waveforms remain stable. Therefore, these two types of waveforms can be regarded as “morphologically stable waveforms”.

The evolution rate of the integrated wind power waveform

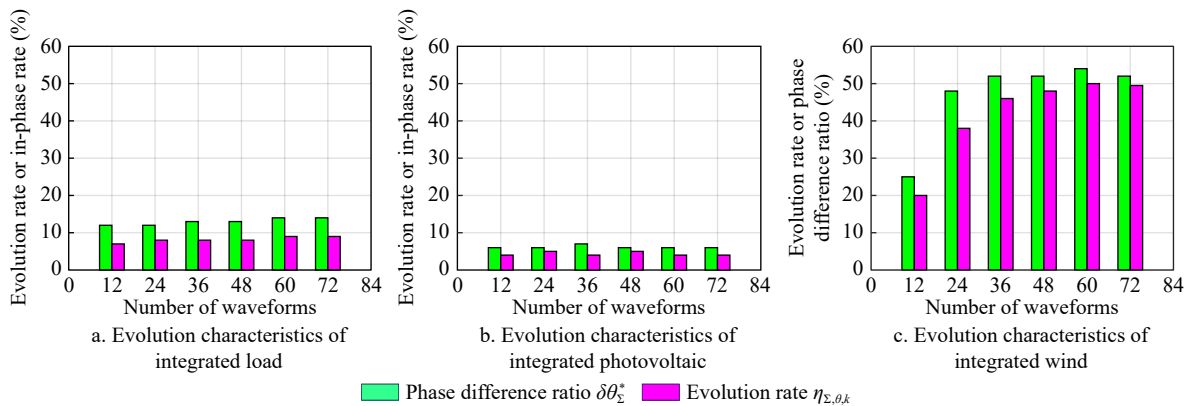


Fig. 5. Phase difference ratio and evolution intensity of integrated waveforms under different numbers of waveforms.

increases with the number of integrated waveforms, showing a trend toward extreme evolution. This is because wind power waveforms are highly stochastic, and the phase-difference rate among multiple waveforms gradually increases as the number of integrated waveforms increases. Therefore, wind power waveforms can be regarded as “morphologically unstable waveforms.”

IV. EVOLUTION CHARACTERISTICS OF INTEGRATED MULTI-TYPE POWER WAVEFORMS IN POWER SYSTEMS WITH INCREASING RENEWABLE ENERGY PENETRATION

According to the analysis in Chapter III, it can be inferred that, in power systems, the phase differences among multiple power waveforms with stable morphology are fixed. Therefore, as renewable energy penetration changes, the evolution characteristics of these integrated waveforms are mainly affected by amplitude differences among waveforms. A typical case is the integration of load and photovoltaic waveforms. If the integrated multi-type waveforms include a waveform type with unstable characteristics, both the phase differences and amplitude differences among waveforms vary with renewable energy penetration. In this case, the evolution characteristics of the integrated waveform are mainly dominated by the unstable waveform type. A typical case is the integration of load and wind power waveforms. Based on the proposed waveform integration evolution analysis method, this Chapter analyzes the variation characteristics of waveform evolution for different waveform types under different penetration levels. The evolution of the peak–valley difference of the integrated waveform is further used as an example to verify the effectiveness of the proposed method.

A. Evolution Characteristics of Integrated Multi-Type Stable-Morphology Waveforms Under Different Proportions

Taking the integration of load and photovoltaic waveforms as an example, integration scenarios under different photovoltaic penetration levels were constructed based on 48 daily load waveform datasets and multiple photovoltaic waveform datasets from a provincial power grid on the same day, sampled at 15-min intervals. These scenarios were used to analyze the evolution trend of the integrated load–photovoltaic waveform.

The photovoltaic penetration ratio of the integrated power waveform is defined as the ratio of the sum of peak–valley differences of all photovoltaic waveforms involved in the integration, $\Delta\tilde{P}_{\Sigma,pv}^{NE}$, to the sum of peak–valley differences of all load waveforms, $\Delta\tilde{P}_{\Sigma,l}^{NE}$, i.e., $\lambda_{pv} = \Delta\tilde{P}_{\Sigma,pv}^{NE} / \Delta\tilde{P}_{\Sigma,l}^{NE}$.

Under different photovoltaic penetration levels, the load and photovoltaic waveforms involved in the integration, as well as the morphologies of the integrated waveforms, are shown in Fig. A1 in the Appendix. The numbers of load and photovoltaic waveforms and their peak–valley difference scales are listed in Table A1 in the Appendix.

Using the integrated peak–valley difference under the in-phase condition of multiple waveforms, $\Delta\tilde{P}_{\Sigma,lp}^{NE}$, as the benchmark, the degree to which the actual peak–valley difference $\Delta\tilde{P}_{\Sigma,lp}$ deviates from $\Delta\tilde{P}_{\Sigma,lp}^{NE}$ is defined as the evolution rate of the integrated waveform peak–valley difference: $\eta_{\Delta,l,pv} = (\Delta\tilde{P}_{\Sigma,lp}^{NE} - \Delta\tilde{P}_{\Sigma,lp}) / \Delta\tilde{P}_{\Sigma,lp}^{NE}$. The metric $\eta_{\Delta,l,pv}$ is used to verify the effectiveness of the load–photovoltaic integration evolution rate $\eta_{l,pv}$ obtained from the analysis in Section B of Chapter III.

In Fig. 6, the blue and purple bars represent the “peak–valley difference superposition of multiple waveforms,” $\Delta\tilde{P}_{\Sigma,lp}^{NE}$, and the actual peak–valley difference of the integrated waveform, $\Delta\tilde{P}_{\Sigma,lp}$, under different photovoltaic penetration ratios, respectively. In Fig. 7, the purple and green bars represent the actual evolution rate of the integrated waveform peak–valley difference, $\eta_{\Delta,l,pv}$, and the estimated integrated waveform evolution rate, $\eta_{l,pv}$, respectively.

The purple bars in Fig. 6 show that, within $0 < \lambda_{pv} \leq 0.5$, the peak–valley difference of the integrated waveform decreases as photovoltaic penetration increases. This is because the increasing photovoltaic waveform amplitude reduces its amplitude difference from the load waveform, thereby enhancing amplitude cancellation evolution between waveforms.

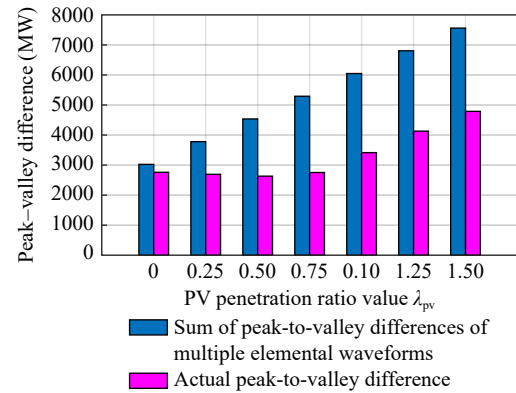


Fig. 6. Peak-to-valley differences of load-photovoltaic integrated waveforms under different photovoltaic penetration rates.

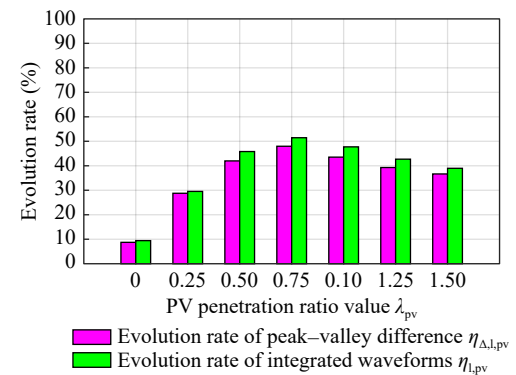


Fig. 7. Evolution rates of load-photovoltaic integrated waveforms under different wind penetration rates.

Within $0.5 < \lambda_{pv} \leq 1.5$, the peak–valley difference of the integrated waveform increases with photovoltaic penetration. This is because the increased photovoltaic amplitude overwhelms the load waveform amplitude, making the integrated waveform characteristics dominated by the photovoltaic waveform.

Fig. 7 shows that the evolution rate of the integrated waveform peak–valley difference, $\eta_{\Delta,l,pv}$, and the integrated waveform evolution rate, $\eta_{l,pv}$, exhibit largely consistent trends with increasing photovoltaic penetration. This verifies that the proposed method can effectively estimate integrated waveform evolution. The purple bars in Fig. 7 show that when $\lambda_{pv} = 0.75$, $\eta_{l,pv}$ reaches its maximum value. This means that, during load–photovoltaic integration, there exists a maximum critical penetration level at which the integrated waveform exhibits the strongest evolution. Understanding the integration evolution pattern of load and photovoltaic waveforms can help optimize the load–photovoltaic ratio and maximize the benefits of regulation resource allocation.

B. Integration Characteristics of Multi-Type Waveforms With Unstable Features

Similarly, integration scenarios of multiple load and wind power waveforms are constructed under different wind power penetration ratios. The wind power penetration ratio is defined as $\lambda_w = \Delta \tilde{P}_{\Sigma,w}^{NE} / \Delta \tilde{P}_{\Sigma,l}^{NE}$. Under different photovoltaic penetration levels, the load and wind power waveforms involved in the integration, as well as the morphologies of the integrated waveforms, are shown in Fig. A2 in the Appendix. The numbers of load and wind power waveforms and their peak–valley difference scales are listed in Table A2 in the Appendix.

In Fig. 8, the blue and purple bars represent the “peak–valley difference superposition of multiple waveforms,” $\Delta \tilde{P}_{\Sigma,lw}^{NE}$, and the actual peak–valley difference of the integrated waveform, $\Delta \tilde{P}_{\Sigma,lw}$, under different wind power penetration ratios, respectively. In Fig. 9, the purple and green bars represent the evolution rate of the integrated waveform peak–valley difference, $\eta_{\Delta,l,w}$, and the estimated integrated waveform evolution rate, $\eta_{l,w}$, respectively.

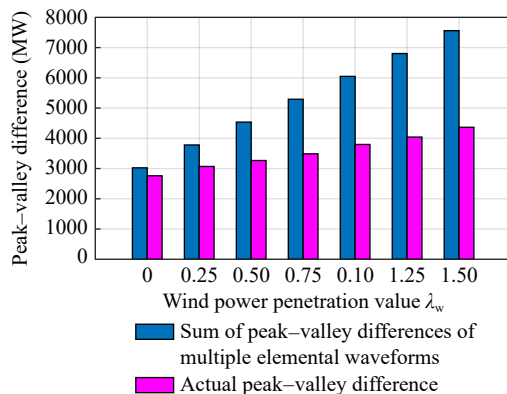


Fig. 8. Peak-to-valley differences of load–wind integrated waveforms under different wind penetration rates.

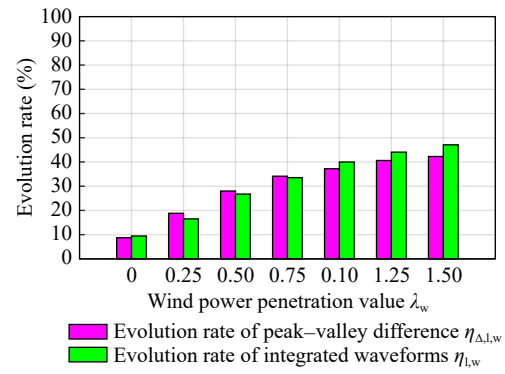


Fig. 9. Evolution rates of load–wind integrated waveforms under different wind penetration rates.

Fig. 8 shows that, as wind power penetration increases, the cancellation of the integrated waveform peak–valley difference $\Delta \tilde{P}_{\Sigma,lw}$ relative to the result under “multivariate superposition,” $\Delta \tilde{P}_{\Sigma,lw}^{NE}$, becomes increasingly large, and the evolution of the integrated waveform peak–valley difference becomes more pronounced. This is caused by the enhanced internal evolution of wind power waveforms as penetration increases.

Fig. 9 shows that both the peak–valley difference evolution rate $\eta_{\Delta,l,w}$ and the integrated waveform evolution rate $\eta_{l,w}$ increase with wind power penetration and are generally consistent. This indicates that, within an acceptable deviation range, $\eta_{l,w}$ can effectively estimate the peak–valley difference of integrated load–wind power waveforms.

The above analysis indicates that understanding the integration evolution law of load and wind power waveforms can avoid overestimating integrated waveform fluctuations and achieve substantial regulation benefits under high penetration levels.

C. Variation Characteristics of the Integration Evolution Intensity of All Passive Power in Power Systems Under Different Renewable Energy Penetration Levels

Based on the case scenarios in Sections A and Sections B of Chapter IV., integrated scenarios of load, photovoltaic, and wind power waveforms are constructed under different renewable energy penetration levels. The total renewable energy penetration ratio is defined as the sum of photovoltaic and wind power penetration ratios, i.e., $\lambda_{p,w} = \lambda_p + \lambda_w$. The photovoltaic share in renewable energy is defined as $\gamma_{pw} = \lambda_p / \lambda_{p,w}$, which reflects the relative proportion of photovoltaic and wind power at the same penetration ratio $\lambda_{p,w}$. The three-dimensional variation trend of the integrated waveform evolution rate $\eta_{l,p,w}$ with the renewable energy penetration ratio $\lambda_{p,w}$ and photovoltaic share γ_{pw} is calculated, as shown in Fig. 10.

It can be seen that, as the photovoltaic share γ_{pw} approaches 1, the variation of the integrated waveform evolution rate $\eta_{l,p,w}$ with $\lambda_{p,w}$ becomes closer to a “decrease–then–increase” trend, indicating pronounced integration characteristics of load and photovoltaic waveforms. As γ_{pw} approaches 0, $\eta_{l,p,w}$ increases with $\lambda_{p,w}$, indicating pronounced integration charac-

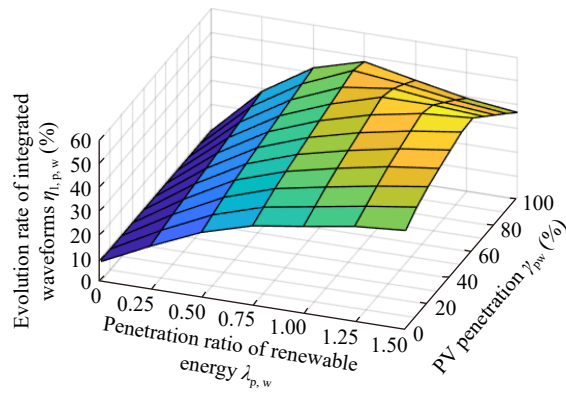


Fig. 10. Variation trend of load-wind-photovoltaic integrated waveform evolution rate with renewable energy penetration and wind-photovoltaic ratio.

teristics of load and wind power waveforms. The photovoltaic share γ_{pw} has a strong regular influence on the evolution intensity of the integrated waveform.

To further analyze the influence of the relative proportions of wind and photovoltaic power on integrated waveform evolution, the variation of the integrated waveform evolution rate $\eta_{l,p,w}$ with the photovoltaic-wind ratio γ_{pw} is analyzed under high renewable energy penetration, $\lambda_{p,w} = 1.5$, as shown in Fig. 11.

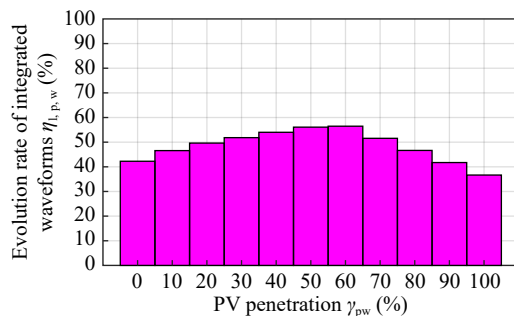


Fig. 11. Characteristics of load-wind-photovoltaic integrated waveform evolution rate under different photovoltaic-wind ratios at high renewable energy penetration.

It can be seen that, as γ_{pw} increases, the integrated waveform evolution rate first increases and then decreases. When $\gamma_{pw} = 60\%$, the evolution rate of the integrated waveform reaches its maximum value. The above analysis shows that understanding the regular evolution trend of integrated load-photovoltaic-wind power waveforms can reduce the overestimation of system regulation requirements under different renewable energy penetration levels. By optimizing the wind-photovoltaic ratio, the maximum benefit of regulation resource savings can be achieved.

V. CONCLUSIONS

To address the supply-demand mismatch in power systems

caused by high renewable energy penetration and to accurately characterize demand for regulation capacity induced by the total passive power waveform, this paper focuses on the key issue of how to reveal the integrated morphology of multiple short-term power waveforms in future power systems. Starting from the characterization of component waveform morphology, the integration evolution morphology of multiple power waveforms is investigated. The main conclusions are as follows:

(1) A multi-timescale amplitude-phase parametric model for power waveforms is proposed. It decomposes and analyzes power waveform morphology from the perspectives of amplitude and phase across multiple timescales, overcoming the limitation of conventional waveform evaluation methods in accurately characterizing local waveform morphology.

(2) For the integration characteristics of multiple power waveforms, the proposed waveform analysis method is used to analyze the phase-difference and amplitude-difference characteristics among multiple waveforms. The mechanism by which these two characteristics affect integrated waveform evolution is revealed, enabling accurate and effective evaluation of the evolution intensity of multivariate integrated waveforms and its multiscale composition.

(3) The proposed evaluation method for multivariate waveform integration evolution enables the assessment of the integration characteristics of both single-type and multi-type waveforms.

(4) The regular evolution trends of the integration characteristics and peak-valley difference characteristics of all passive power waveforms in the system with increasing renewable energy penetration are revealed. This has important engineering value for accurately characterizing the fluctuation morphology of integrated waveforms under different penetration levels, optimizing regulation resources allocation, and saving regulation resources.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AI USAGE STATEMENT

During the preparation of this manuscript, the authors used AI-assisted tools for language polishing only. The authors have reviewed and edited the content and take full responsibility for the final version of the manuscript.

APPENDIX

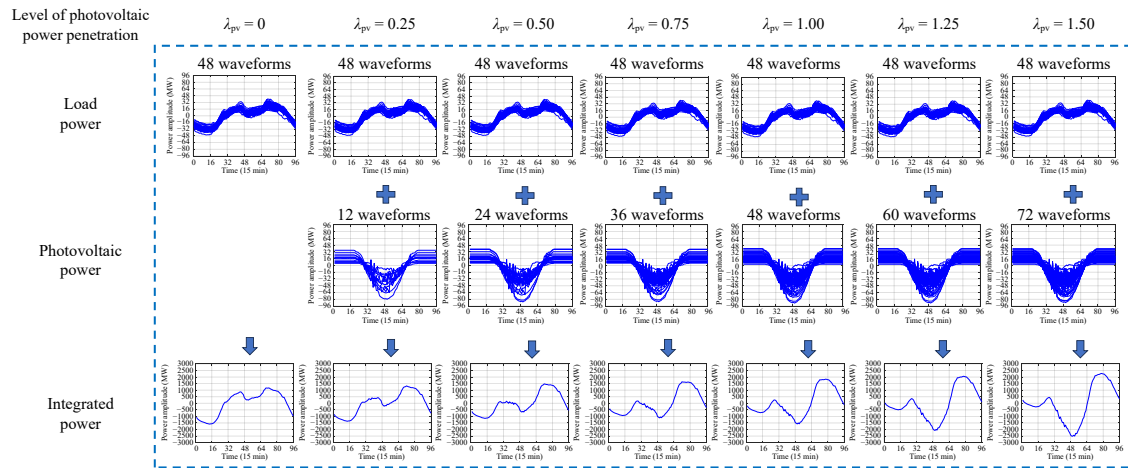


Fig. A1. Integration scenarios of multiple load and photovoltaic waveforms under different photovoltaic penetration ratios.

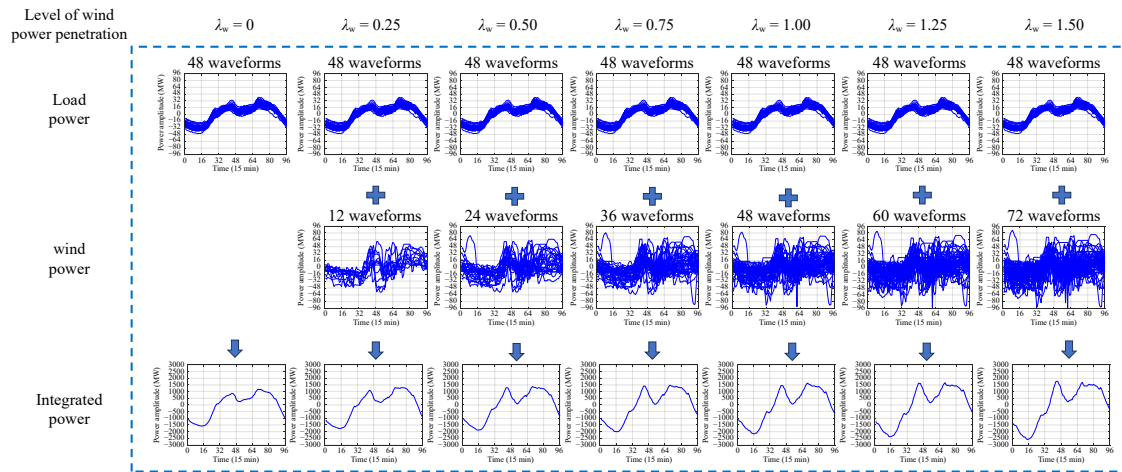


Fig. A2. Integration scenario of multi-type load and wind power waveforms with different wind penetration levels.

TABLE A1
WAVEFORM PARAMETERS OF LOAD AND PHOTOVOLTAIC UNDER DIFFERENT PHOTOVOLTAIC PENETRATION LEVELS

$\Delta \bar{P}_{\Sigma, l}^{NE}$ (MW)	3024	3024	3024	3024	3024	3024	3024
Number of load waveforms n_l	48	48	48	48	48	48	48
$\Delta \bar{P}_{\Sigma, pv}^{NE}$ (MW)	0	756	1512	2268	3025	3780	4536
Number of PV waveforms n_{pv}	0	12	24	36	48	60	72
λ_{pv}	0	0.25	0.5	0.75	1	1.25	1.5

TABLE A2
WAVEFORM PARAMETERS OF LOAD AND WIND UNDER DIFFERENT WIND PENETRATION LEVELS

$\Delta \bar{P}_{\Sigma, l}^{NE}$ (MW)	3024	3024	3024	3024	3024	3024	3024
Number of load waveforms n_l	0	756	1512	2268	3025	3780	4536
$\Delta \bar{P}_{\Sigma, w}^{NE}$ (MW)	0	63	63	63	63	63	63
Number of wind waveforms n_w	0	12	24	36	48	60	72
λ_w	0	0.25	0.5	0.75	1	1.25	1.5

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