Renewable and Sustainable Energy Reviews 217 (2025) 115794

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

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

Evaluating inertia estimation methods in low-inertia power systems: A comprehensive review with analytic hierarchy process-based ranking

Mohamed Abouyehia [a,b,*], Agustí Egea-Àlvarez [a], Khaled H. Ahmed [a]

[a] Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, G1 1XQ, UK
[b] Department of Engineering Mathematics and Physics, Faculty of Engineering, Alexandria University, Alexandria, 21544, Egypt

ARTICLE INFO

Keywords:
Inertia estimation
Low-inertia system
Data-driven estimation methods
RoCoF
PMU

ABSTRACT

This paper provides a comprehensive review of inertia estimation methods, with a particular emphasis on the challenges posed by the integration of renewable energy sources (RESs). It examines a broad spectrum of inertia estimation methods, ranging from traditional swing equation-based methods to cutting-edge advancements such as machine learning and real-time analytics. These estimation methods are systematically categorised and evaluated based on key performance metrics including accuracy, simplicity, computational efficiency, and robustness against noise. The analytic hierarchy process (AHP) is used to identify the most suitable methods for low-inertia systems with high renewable energy penetration. The evaluation also includes an assessment of the temporal operational modes and the implementation requirements for the estimation methods. This leads to detailed recommendations on the most appropriate application environments for each method, considering factors such as system scale and generation mix. Existing challenges and future directions related to inertia estimation are also discussed.

1. Introduction

In the dynamic landscape of power systems, inertia is a fundamental concept integral to grid stability [1,2]. Traditionally, power system inertia predominantly originated from thermal and hydroelectric power plants, which are characterised by their predictable operations. Consequently, inertia estimation methods for these plants, typically based on swing equations, have been considered both accurate and reliable [3]. However, as the energy sector evolves, particularly with the integration of renewable energy sources characterised by less predictable operations, these traditional estimation methods face increasing limitations in terms of accuracy and adaptability [4,5]. These limitations have driven the development of cutting-edge advancements in inertia estimation that can effectively address the complexities introduced by renewable integrations [6].

In light of the growing complexity of power systems, it is imperative to thoroughly review and evaluate inertia estimation methods. Despite the importance of this assessment, comprehensive reviews on this topic remain limited. For instance, the review in Ref. [7] focuses primarily on traditional rate of change of frequency (RoCoF)-based estimation methods. However, it lacks a broader analysis of advanced estimation methods, such as machine learning. On the other hand, the review in Ref. [8] explored a broader spectrum of estimation methods, expanding beyond the RoCoF-based methods. However, it does not provide a detailed evaluation of key performance metrics for the estimation methods such as accuracy and computational complexity. Although [9] evaluates key performance metrics for estimation methods, such as accuracy, it does not cover a wide range of methods, which leaves a gap in comprehensively addressing both traditional methods and those suited for low-inertia grids.

From another perspective, some review papers assess the efficiency of each estimation method in operating across various temporal operational modes, such as offline, online, and forecasting [6,10,11]. For instance, the review in Ref. [10] examines the temporal operational modes of inertia estimation methods, but does not include a comprehensive range of estimation methods nor a detailed evaluation across other important performance metrics, such as accuracy and computational time. Similarly, although [6] covers range of estimation methods, it does not provide a comprehensive evaluation of the implementation requirements for these methods or their key performance metrics, which are essential for low-inertia systems. Finally, the review in Ref. [11] primarily evaluates estimation methods based on their temporal

* Corresponding author. Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, G1 1XQ, UK.
E-mail address: mohamed.aboyehia@strath.ac.uk (M. Abouyehia).

https://doi.org/10.1016/j.rser.2025.115794
Received 12 December 2024; Received in revised form 10 April 2025; Accepted 25 April 2025
Available online 28 April 2025

operational modes and implementation requirements. However, it also lacks a detailed analysis of the methods themselves, including their performance metrics, advantages, and disadvantages Additionally, it fails to offer a clear categorisation of these methods.

In summary, existing reviews on inertia estimation methods include several notable gaps. Many of these reviews have a limited scope, focusing on a narrow range of estimation methods and often overlooking advanced estimation methods, such as machine learning and other data-driven methods. Additionally, the lack of a comprehensive classification of estimation methods in many studies results in an incomplete understanding of the full capabilities of these methods. While some reviews evaluate estimation methods based on temporal operational modes or their implementation requirements, they often fail to provide a thorough evaluation of their key performance metrics critical for low-inertia systems, such as accuracy, computational efficiency, simplicity, real-time capability, and robustness to noise. Moreover, these reviews fail to specify the optimal conditions or recommended environments for the application of each method, leaving a significant gap in practical guidance.

This paper aims to address these significant gaps by providing a comprehensive review of inertia estimation methods. It introduces a novel systematic classification of a broad range of inertia estimation methods, from traditional approaches to advanced machine learning and other data-driven based methods. Additionally, the review examines over 130 articles and evaluate each inertia estimation method based on key performance metrics such as accuracy, simplicity, computational efficiency, and robustness against noise. The methods are ranked based on these performance metrics using an AHP-based approach to determine the most appropriate method for low-inertia power systems. Beyond the performance metrics, the evaluation extends to assess the methods against different temporal operational modes and identify their implementation requirements, which provides insights into the optimal environments for each method. The paper also explores key challenges and outlines future research directions in inertia estimation, particularly in the contexts of renewable integration.

The paper is organised as follows. Section II explores the fundamental principles of inertia and momentum in power systems. Section III provides a systematic classification of inertia estimation methods and discusses their main concepts, along with their advantages and disadvantages. Section IV presents a comprehensive evaluation of these methods, assessing them based on key performance metrics. It also evaluates the estimation methods against different temporal operational modes and their implementation requirements. Section V ranks the methods using the AHP to identify the most suitable methods for low-inertia systems, and provides recommendations on the optimal environments for each method. Section VI focuses on special topics in inertia estimation, including contributions in the literature related to the estimation of synthetic and virtual inertia, as well as the indirect estimation of inertia through the analysis of electromechanical modes. Finally, section VII discusses the challenges associated with inertia estimation and outlines potential directions for future research.

2. Essential principles of physical inertia, synthetic inertia and momentum

This section introduces the fundamental concepts of physical inertia, synthetic inertia, and angular momentum within the context of power system dynamics, and establishes the mathematical relationship between inertia and angular momentum.

2.1. Physical inertia

Physical inertia fundamentally captures the stored kinetic energy within the revolving mass of all machines directly connected to the power system. This stored energy acts as an immediate buffer against sudden power imbalances and plays a vital role in determining how quickly the system frequency changes following a disturbance. The inertia constant H (in seconds) characterises this kinetic energy per unit of rated apparent power [19]. Accordingly, for a machine with rated apparent power S (in MVA), the total stored kinetic energy E_k (in MVA.s) is expressed as:

$$E_k = S^*H \tag{1}$$

Moreover, the inertia constant can be expresses in terms of the machine physical parameters as:

$$S^*H = \frac{1}{2}J\omega^2 {}^* 10^{-6} \tag{2}$$

where, J is the moment of inertia of the rotating parts (in kg.m^2), and ω is the synchronous angular speed in mechanical radians per second. These expressions show that, the total kinetic energy increases as the inertia constant H increases. In other words, a higher inertia constant indicates that more energy is stored in the rotating mass.

The ongoing shift toward renewable energy sources is dramatically altering the inertia landscape. Fig. 1(a) presents the total stored kinetic energy in GVA·s from synchronous machines connected to the national grid, which has been decreasing over recent years. As traditional fossil-fuel generators are replaced by renewable sources such as wind and solar, along with increased HVDC imports, fewer synchronous machines remain connected. This results in reduced stored kinetic energy and, consequently, lower system physical inertia [12,13]. Moreover, insufficient physical inertia within the power grid makes it challenging to maintain frequency within its normal range. This insufficiency can heighten the risk of power outages, and widespread blackouts [14,15]. This is clearly illustrated in Fig. 1(b), which shows the higher RoCoF in low-inertia systems.

2.2. Synthetic inertia

Synthetic inertia, often referred to as virtual inertia, replicates the effect of rotational kinetic energy by allowing inverter-based resources (IBRs) to respond inherently and almost instantaneously to changes in grid frequency. Unlike conventional synchronous generators, which naturally provide inertia through the momentum of their rotating masses, synthetic inertia is delivered by grid-forming converters. A key advantage of these converters is their ability to maintain an internal frequency reference independent of the grid. When a disturbance occurs, the grid frequency begins to diverge from the inverter internal frequency, creating a phase angle difference that drives an immediate exchange of active power (closely mimicking the inertial response of a synchronous machine). This response typically occurs within 20 ms and does not depend on frequency measurement or external control triggers. Instead, it arises from the inherent interaction between two voltage sources operating at slightly different frequencies. While synthetic inertia is highly effective in stabilizing frequency during the critical first moments of a disturbance, its performance can be limited by inverter current constraints and the complexity of tuning advanced control algorithms [16]. One of the primary challenges in estimating synthetic inertia lies in the relatively rapid nature of the fast frequency response (FFR) provided by grid-forming converters. Because FFR occurs within milliseconds, it is difficult to distinguish the true inertial effect from FFR. Therefore, any method developed to estimate synthetic inertia must be capable of operating with high temporal resolution and accurately isolating the inertial component from overlapping control-based responses, such as FFR. This is particularly important in modern power systems with high shares of inverter-based resources [17].

Table I outlines several factors that directly influence the system overall inertia, including both physical and virtual, along with its impact on the RoCoF.

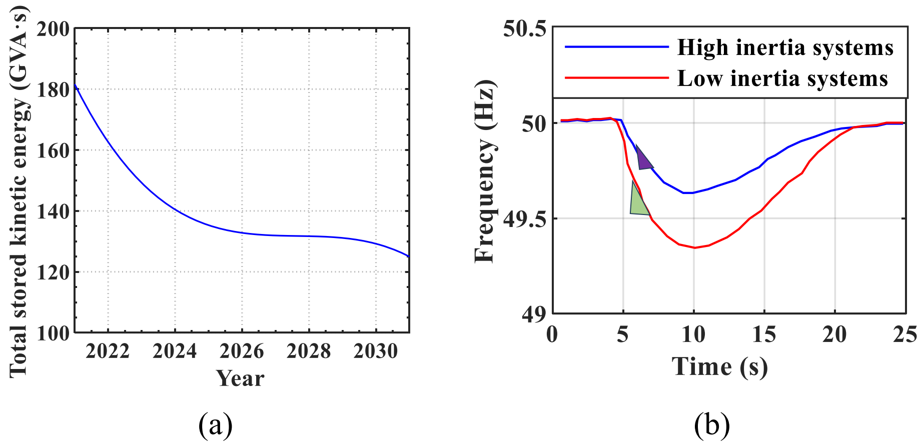

Fig. 1. Impact of the energy transition on system kinetic energy and frequency dynamics: (a) reduction in total stored kinetic energy due to displacement of synchronous generation, and (b) corresponding increase in the RoCoF in low-inertia power systems.

Table 1
Summary of factors influencing system inertia and resulting RoCoF behaviour [18].

Factor	Impact on power system inertia
Generator physical inertia	A reduction in generator inertia lowers the overall system inertia, which results in a higher RoCoF immediately after a disturbance.
Load inertia	A reduction in load-side rotating masses, such as industrial motors, decreases the overall system inertia, leading to an increased RoCoF immediately following a disturbance.
Synthetic/virtual inertia	A reduction or absence of synthetic/virtual inertia limits the system ability to emulate inertial response, causing a sharper RoCoF and greater frequency deviation immediately after a disturbance.

2.3. Momentum

Angular momentum is another key concept in power system dynamics and is defined as the product of the moment of inertia and the synchronous angular speed of the rotating mass. Mathematically, the angular momentum M (in MJ·s/rad or kg·m^2.rad/s) is given by Ref. [19]:

$$M = J\omega \tag{3}$$

Angular momentum represents the system ability to resist changes in rotational speed. Similar to inertia, it plays a critical role in maintaining frequency stability following a disturbance. There is a direct relationship between the inertia constant H and angular momentum M. This relationship is given by $M = \frac{2HS}{\omega}$, which highlights that inertia constant and angular momentum are inherently linked through the synchronous angular velocity. Consequently, some studies in the literature focus on estimating angular momentum, while others estimate the inertia constant. The choice between the two often depends on the modelling framework and available measurement data. Nonetheless, given their direct mathematical equivalence through the synchronous angular velocity, both inertia and angular momentum convey the same essential information regarding the system dynamic behaviour.

3. Classification of inertia estimation methods

The methods for inertia estimation are diverse, ranging from traditional analytical methods to advanced machine learning approaches.

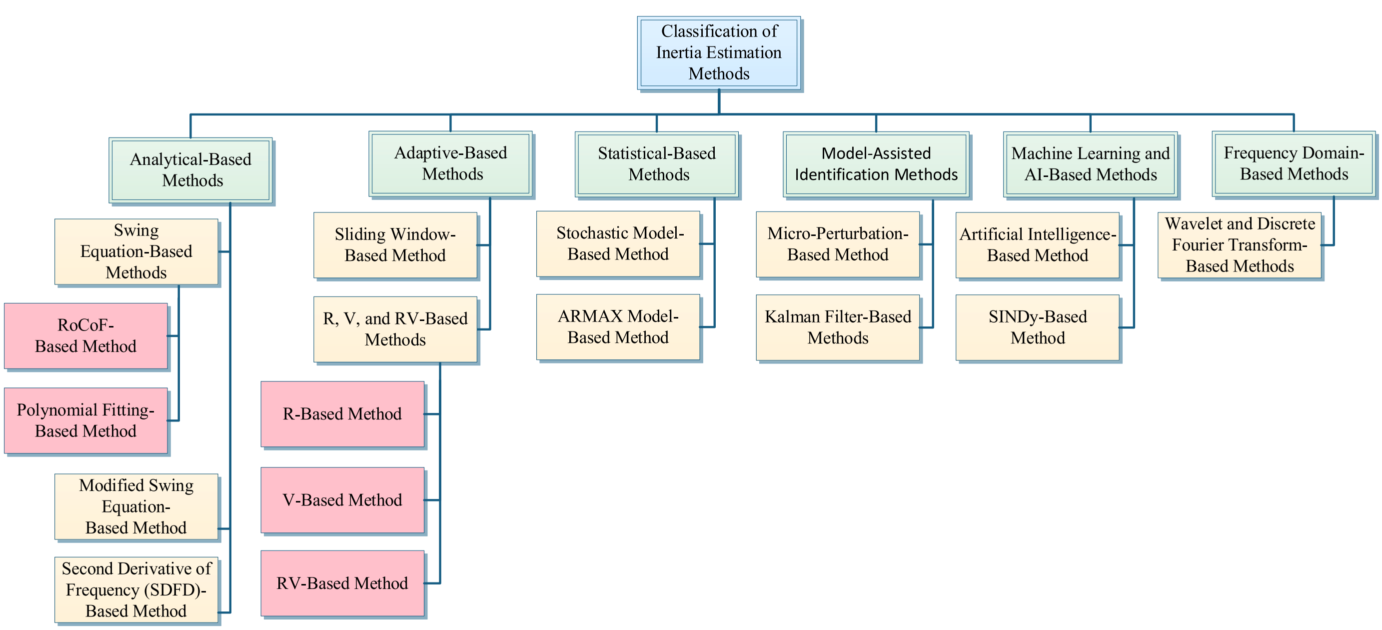

Fig. 2. Comprehensive classification of inertia estimation methods.

These methods can be categorically organised based on their underlying principles. As depicted in Fig. 2, inertia estimation methods are classified into six main categories such as analytical-based methods, adaptive-based methods, statistical-based methods, model-assisted identification methods, machine learning-based methods, and frequency domain-based methods. The following sub-sections provide a detailed discussion of each method, outlining their core concepts and highlighting their respective strengths and limitations.

3.1. Analytical-based estimation methods

Analytical-based methods refer to inertia estimation techniques that rely on first-principles and explicit mathematical formulations derived from the physical laws governing power system dynamics. These methods excel in environments with synchronous generators due to their well-defined dynamic equations. They use predictable generator behaviours and established equations, such as the swing equation, to accurately estimate inertia. These methods can be sub-classified as follows.

a. **Swing Equation-Based Estimation Methods**

The swing equation is a fundamental analytical method used in estimating power system inertia. This method excels in estimating the rotational inertia for synchronous generator rotors. It utilises a differential equation to analyse the power system frequency response following an electrical disturbance, which is mathematically expressed as:

$$\frac{2HS}{f_0}\left(\frac{df}{dt}\right) = P_m - P_e \tag{4}$$

where, f_0 represents the nominal frequency. P_m and P_e are the mechanical and electrical power outputs of the generator, respectively. The variable f corresponds to the actual measured frequency.

The accuracy of swing equation-based methods relies heavily on precise frequency measurements, as outlines in (4). There are various methods to capture and analyse frequency changes in power systems after disturbances. Consequently, swing-equation-based estimation methods are categorised further based on the different approaches used to measure frequency, as follows.

- *Rate of Change of Frequency (RoCoF)-Based Estimation Method*

This method calculates frequency and its rate of change (RoCoF) from PMU data, then applies (4) to estimate inertia. This method is activated when the absolute RoCoF exceeds a predetermined threshold. Consequently, it excels in environments with significant disturbances, such as step loading and generator outages, which impact the RoCoF response and trigger the estimation method. Table II summarises various RoCoF-based methods referenced in the literature, and highlights their strengths and weaknesses.

In summary, RoCoF-based methods are simple and suitable for real-time inertia monitoring due to their ability to provide rapid feedback on inertia changes. However, the accuracy of RoCoF-based inertia estimation is sensitive to the selection of the threshold value, and an inappropriate threshold might lead to inaccurate results. Moreover, this method relies solely on frequency and power measurements and potentially overlooking the other factors, such as system damping.

- *Polynomial Fitting-Based Estimation Method*

Polynomial fitting is another swing-equation-based method that provides more stable frequency calculations than the RoCoF method. This method avoids potential numerical instabilities that arise in RoCoF methods when calculating inertia (H) in (4), particularly due to the division by the frequency derivative, which may approach zero. Therefore, polynomial fitting excels in environments characterized by rapid frequency changes and high noise levels [23,24]. The operational framework of the polynomial fitting process is illustrated in Fig. 3. This method utilises the measured frequency deviation (Δf) from PMU data. It selects an appropriate polynomial order for frequency deviations, typically fifth-order for inertia applications [25]. The A_1 coefficient from the polynomial fitting (highlighted in red in Fig. 3) effectively maps the derivative of frequency in (4) without numerical issues, as further described in Ref. [25]. Inertia estimation is then performed using this coefficient instead of relying on derivative action. Table III summarises the application of polynomial fitting methods to PMU data for

Table 2
Summary of RoCoF-based methods in literature.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[20]	Relies on RoCoF calculations using wide-area frequency monitoring	Calculates RoCoF based on the 0.5-s frequency change following a disturbance. It is simple but less accurate with small disturbances. Proven effective in large systems such as the U.S. eastern interconnection system.
[21]	Relies on RoCoF using local PMU frequency measurements	Does not need for wide-area frequency monitoring. Demonstrates high accuracy with estimation errors showing a mean of −0.7 %. Proven effective in moderate system sizes such as the IEEE 39-bus test system.
[22]	Relies on RoCoF using PMU and synchrophasor measurements	Utilises synchrophasor data to estimate the inertia in real-time. It is accurate but requiring computational resources. Proven effective in moderate system sizes such as the 39 bus New England system.

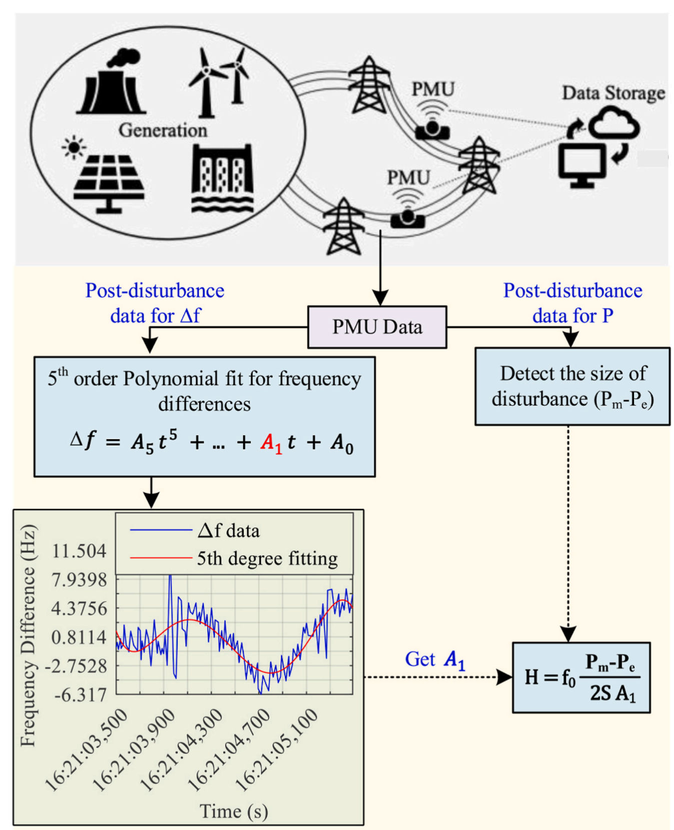

Fig. 3. Inertia estimation using polynomial fitting.

Table 3
Summary of polynomial fitting methods in PMU data analysis.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[24]	Utilises fixed-order polynomial fitting for frequency smoothing (first-order fitting for linear ranges, and second for parabolic ranges)	Proposes an offline and simple estimation. Effective in systems with low noise levels but may struggle with larger disturbances. Proven effective in moderate system sizes such as Nordic32 test system.
[27]	Applies fifth-order polynomial approximation while considering the load dynamics	Minimizes oscillatory effects. Requires more computational resources due to higher-order fitting. Proven effective in large system sizes such as Taiwan power system.
[28]	Applied fifth-order polynomial fitting for PMU data	Provides robust inertia estimates against high renewable penetration. High computational complexity and sensitivity to data quality. Proven effective on large system sizes such as Japanese power system.
[29]	Applied fifth-order polynomial fitting for systems with virtual inertia techniques	Estimates virtual inertia of systems with high wind integration. The accuracy is low about 85–90 %. Proven effective in small power system model.
[30]	Uses variable-order polynomial curve fitting with least squares adjustment	Accurate and robust inertia estimation. Sensitive to the correct selection of polynomial order which affects accuracy. Proven effective in a small custom IEEE standard distribution system with solar PV.

estimating frequency deviations without numerical issues.

In summary, the polynomial fitting adapts well to the dynamic frequencies observed in large, interconnected power systems, which makes it more reliable in complex scenarios. However, the additional curve fitting processes may introduce computational demands. Moreover, the time required for identifying the appropriate polynomial order and fitting the curve may cause a slight delay in obtaining inertia estimates compared to RoCoF-based method. These challenges make it more suitable for offline estimation.

b **Modified Swing Equation-Based Estimation Method**

This method is another analytical estimation approach that excels in environments with complex dynamics, particularly in medium power systems that have a diverse generation mix [26]. This improved formula is developed to address the numerical issues in (4) by avoiding division by derivative calculations, similar to the polynomial fitting. In summary, this method provides a rapid and robust framework for real-time estimation. It effectively manages frequency variations and external disturbances in stable manner. However, this improved formula is sensitive to the selection of specific parameters, which require optimal tuning and potentially result in increased computational time.

c **Second Derivative of the Frequency (SDFD)-Based Estimation Method**

$$\frac{2HS}{f_0}\left(\frac{df}{dt}\right)=P_m-P_e-D_G(f-f_0) \tag{5}$$

The swing equation, as initially presented in (4), does not fully includes the complexities of power system dynamics, such as damping effects. However, this method is another analytical estimation method but provides a refined representation in (5), which integrates the damping effect.

where, D_G represents the damping constant. The formulation in (5) is further simplified to (6), as discussed in Ref. [26]:

$$H=-f_0\frac{dP_e}{dt}\Big/2S\left(\frac{d^2f}{dt^2}\right) \tag{6}$$

This method excels in systems with slow dynamics, particularly in generator-dominated power systems that exhibit large inertia. It is simple and can estimate the system inertia after disturbances by only analysing the frequency second derivative [31,32]. This method, though relatively uncomplicated, depends on a disturbance occurrence (offline). It faces challenges, especially numerical issues when the denominator (representing the second derivative of the frequency) approaches zero [26]. To address this challenge, the use of an inflection point detector (IPD) has been suggested [33,34]. Fig. 4(a) shows how IPD eliminates the zero crossing in the second derivative of frequency by tracking points on a measured frequency curve where the second derivative crosses zero (inflection points). It then connects these points to obtain an approximate RoCoF without inflection points, thus allowing for the system inertia to be estimated without numerical issues. Fig. 4(b) compares the SDFD versus IPD in inertia estimation, where SDFD produces numerical issues while IPD does not.

3.2. Adaptive-based estimation methods

This section discusses the adaptive methods for estimating inertia in power systems. These methods use real-time adaptive algorithms to enhance the accuracy and responsiveness of inertia estimation under varying operational conditions. These methods can be sub-classified as follows.

a. **Sliding Window-Based Estimation Method**

The sliding window method is an adaptive method that provides a robust inertia estimation, particularly excelling in real-time applications involving generator mixes with fast dynamics. This method is accurate as it employs a series of sequential data points within a defined window size (N) to compute the mean value, rather than depending on a single point measurement [35]. This window is applied sequentially over the input data in a sliding manner to estimate the inertia [36]. Various methods in the literature utilise the sliding window approach which are summarized in Table IV.

In summary, sliding window-based estimation methods surpass in precisely tracking the inertia constant in real-time. However, they face challenges such as reliance on accurate data, computational intensity, and sensitivity to power system conditions. Moreover, the effectiveness of these methods depends on the optimal chosen window size, with potential issues arising from data noise sensitivity and changes in dynamics over time.

b **R, V, and RV-Based Estimation Methods**

These methods are adaptive estimation approaches that excel in environments with large loads characterized by significant dynamics. Inertia estimation is significantly influenced by the characteristics of active power loads. Despite this important factor, the majority of inertia estimation methods do not account for these characteristics. However, the R, V, and RV-based estimation methods do consider these characteristics [41]. These methods take into account various models of load behaviour, including constant loads, frequency-dependent loads, voltage-dependent loads, and hybrid models that integrate both frequency and voltage dependencies, as follows:

$$\Delta P(t)=h_1(f(t))+h_2(v(t)) \tag{7}$$

where, $\Delta P(t)$ represents the change in active power load. The function $h_1(f(t))$ models the impact of frequency variations on the active power. Conversely, $h_2(v(t))$ is responsible for modelling the impact of voltage

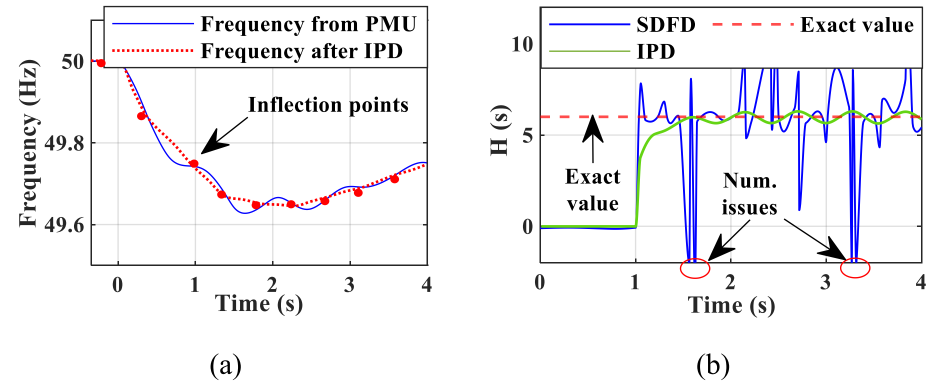

Fig. 4. Inflection point detector method, (a) eliminating zero crossing points in the second derivative of frequency using IPD, and (b) inertia estimation using IPD vs SDFD.

Table 4
Summary of sliding window methods in inertia estimation.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[35]	Combines sliding window method with RoCoF calculations	Proves accuracy and adaptability to varying grid conditions. Complex due to data processing and dependent on precise real-time data. Proven effective on small systems such as EEE 9-bus system.
[36]	Utilises multiple smoothing sliding windows for both active power and RoCoF before and after disturbance	Precision in capturing RoCoF and active power dynamics. The variability in PMU performance, affecting the reliability of inertia estimates. Proven effective on small systems.
[37]	Incorporates a fixed-size sliding window updated periodically for inertia tracking under normal conditions	Provides real-time tracking of inertia under normal conditions. Reliance on high-quality PMU data, which can be prone to noise and inaccuracies. The method demonstrates an error below 5 %. Proven effective in moderate system sizes such as the IEEE 39-bus system.
[38]	Incorporates a sliding window used for regional inertia estimation of power systems with high wind power penetration	Enhances accuracy in wind-integrated power systems. Relies on the precise selection of measurement nodes and robust data processing, potentially increasing computational complexity. Proven effective in moderate system sizes such as the IEEE 39-bus test system.
[39]	Implements dynamic window length adjustment based on disturbance size	Provides robust and real-time inertia estimation without requiring a detailed model of the grid. Depends heavily on the quality and synchronization of input data from PMUs. Proven effective in small benchmark power grids.
[40]	Implements an adaptive sliding window method with variable lengths using least squares and median filtering	Highly accurate estimates that facilitate better control and stability in low inertia grids. Relies on consistent high-quality data and specific window size settings that may not generalize across different system conditions. Proven effective in moderate system sizes such as Hawaiian islands.

changes on the active power. According to these load dynamics, three adaptive inertia estimation methods depend on (7) are introduced:

- *R-Based Estimation Method*

This method focuses on frequency-driven power deviations. It utilises the function $h_1(f(t))$ for estimation. This method does not require voltage data and bypass the complexities associated with voltage dependency [24,27].

- *V-Based Estimation Method*

This method prioritizes voltage variations, using the function $h_2(v(t))$ to measure power deviations resulting from voltage-dependent loads. It does not directly account for frequency effects, therefore; its efficiency highly dependent on the accuracy of the chosen load mode [27,42].

- *RV-Based Estimation Method*

This method combines the R and V methods. It addresses both voltage and frequency variations through $h_1(f(t))$ and $h_2(v(t))$ and offers a comprehensive inertia estimation framework [27,41,43]. Comparative analysis of these methods is shown in Table V.

In summary, these estimation methods offer an advantage over other methods by accounting for the impact of load dynamics on inertia estimation. However, they face challenges in accurately assessing the effects of frequency and voltage variations. To address this issue, an optimization-based approach using particle swarm optimization (PSO) is employed to determine the optimal contribution of $h_1(f(t))$ and $h_2(v(t))$ on active power changes [44].

3.3. Statistical-based estimation methods

Through the application of statistical data analysis, these methods

Table 5
Comparative analysis of R, V and RV based estimation methods [6,27,41].

	R method	V method	RV method
Data required for estimation	Frequency dynamics	Voltage dynamics	Combination of frequency and voltage dynamics
Sensitivity to noise	Low	Moderate	High
Accuracy (%)	≈85–90 %	≈85–90 %	≈95 %
Computational time	Low (millisecond to seconds)	Low (milliseconds to seconds)	Moderate (seconds to tens of seconds)
Implementation complexity	Low	Low	Moderate
Limitations	Does not account for the impact of voltage changes on dynamics	Effectiveness depends on the accuracy of the load model to voltage	Challenges arise in precisely evaluating the contribution of frequency and voltage variations to the load model

improve the accuracy and responsiveness of inertia estimation under varying operational conditions. They excel in complex systems with RESs due to the unpredictable nature of their behaviour. The statistical characteristics of RESs can be modelled using either stochastic models or the ARMAX model, as outlined below.

a. **Stochastic Model-Based Estimation Methods**

Stochastic model-based estimation methods are particularly excel for inertia estimation in large power systems with high renewable energy penetration. They effectively manage the variability and uncertainty inherent in these environments. Particularly, these methods handle the complex stochastic relationships and time-dependent interactions between system frequency and inertia in RESs [9]. They also capture the random fluctuations in system dynamics, and provide accurate inertia estimates even under small disturbances and normal conditions. Several methods in the literature utilise stochastic processes for inertia estimation, as summarized in Table VI.

In summary, these methods provide real-time inertia estimation under normal conditions, moving beyond swing equation-based methods that focus solely on post-disturbance analysis. However, implementing and operating this stochastic model requires a deep understanding of statistical methods and substantial computational resources. The accuracy of these methods are heavily dependent on the quality and completeness of the input data; poor data quality can lead to unreliable estimates. Additionally, their efficiency rely on careful selection and tuning of the stochastic parameters.

b. **AutoRegressive Moving Average with eXogenous inputs (ARMAX) Based Estimation Method**

The ARMAX model is another statistical-based method, that excels particularly well in medium-sized power systems with a high penetration of RESs. It models the system output as a combination of three types of regression terms: contributions from past inputs, past outputs, and past disturbances or noise [49]. This allows for a more dynamic and comprehensive approach, that accommodates the inherent variability in RES-dominated systems. Fig. 5 illustrates the operational framework of ARMAX method, which captures the dynamics of disturbances to predict the frequency deviation (Δf) at each time step (k). This method predicts the current Δf(k) using past frequency deviations and both past and current input changes in power (Δp), while also accounting for non-measurable or noise inputs (e) from both current and previous time steps. The ARMAX model parameters, a_i, b_i, and c_i include the autoregressive (AR), moving average (MA), and exogenous input (X) influences, respectively, and need to be precisely estimated. To optimally estimate these model parameters, the predicted Δf is compared with the actual measured Δf to generate an error signal. The ARMAX model parameters are iteratively refined to minimize this prediction error when it exceeds a predefined threshold value ($\approx 10^{-3}$). These parameters are then utilised for inertia estimation [50]. Various methods in the literature utilise the ARMAX model, which are summarized in Table VII.

In summary, ARMAX is robust and uses real-time or possibly noisy data for its calculations. However, constraints such as the need for large data windows and higher relative errors in the estimation of some parameters pose convergence challenges. Additionally, all ARMAX-based methods are heavily dependent on the tuning parameters of the ARMAX, which may be a constraint in real-world applications.

Table 6
Summary of stochastic model-based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[45]	Utilises a first-order autoregressive stochastic model with a logistic distribution	Enhances the accuracy by modelling inertia as a combination of logistic and stochastic components. Relies on detailed and accurate historical data for model calibration. Proven effective in large system sizes such as Italian transmission network.
[46]	Utilises a stochastic covariance matrix approach	Does not require disturbances for estimation. Requires consistent high-quality measurements and a detailed model of the grid. Proven effective in large system sizes such IEEE 39-bus system and a 1479-bus model of the all-island Irish transmission system.
[47]	Utilises a stochastic process for online estimation in power systems with high renewable penetration	Accurately predicts the inertia changes, crucial for maintaining grid stability with high renewable penetration. Reliance on extensive real-time data which can be challenging to gather consistently. Proven effective in large system sizes such as Italian power grid.
[48]	Dynamic system inertia estimation using switching Markov Gaussian stochastic models	The method excels in continuous real-time inertia estimation with a mean squared error within 0.1 of the variance. Relies heavily on consistent, high-quality measurement data. Proven effective in large system sizes such as UK system.

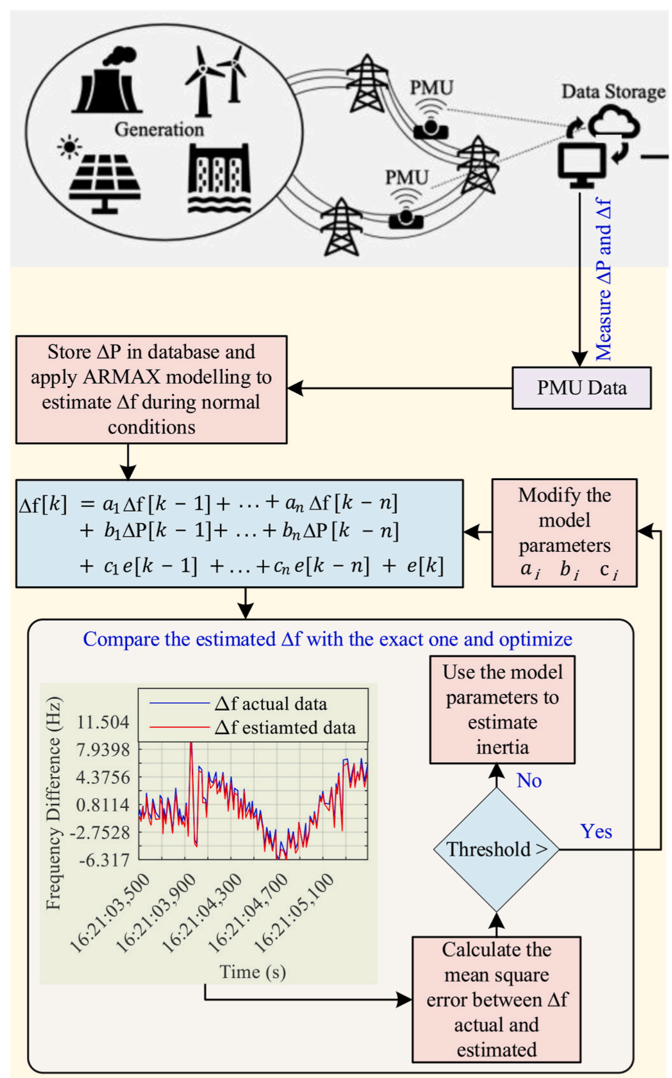

Fig. 5. ARMAX method for inertia estimation.

Table 7
Summary of ARMAX model-based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[51]	Uses a low-order ARMAX model for estimation based on synchrophasors measurements	Offers fast, dynamic inertial constant estimation with low computational complexity. Requires high-quality data and is sensitive to noise and outliers. Proven effective in moderate system sizes such as IEEE 68-bus system.
[52]	Applies ARMAX model for regional inertia estimation	Accurately tracks regional inertia shifts due to renewable integration and dynamic loads. Dependent on the availability and precision of synchrophasor data, which can vary. Proven effective in moderate system sizes such as IEEE 68-bus system.
[53]	Employs ARMAX for equivalent inertia estimation under small disturbances	Provides a stable, continuous estimation method that integrates smoothly into operational practices. Requires consistent, high-quality data for accurate inertia modelling. Proven effective in small models such as single wind turbine.
[54]	Implements ARMAX with time-domain vector fitting	Provides precise inertia constants from normal operating condition data and transient responses without extensive computational demand. Susceptible to noise which can significantly affect the accuracy. Proven effective in moderate system sizes such as IEEE 9 and IEEE 39-bus system.
[55]	Inertia estimation at specific node or system levels using ARMAX with recursive maximum likelihood method	Offers high-resolution inertia estimates critical for grid stability under varying conditions. Requires precise data input and is computationally intensive. Proven effective in moderate system sizes such as IEEE 39-bus system.

Table 8
Summary of micro-perturbation-based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[56]	Injects a small perturbation signal through a power electronic interface. Frequency and active power responses are measured and used to identify a first-order transfer function for estimating the equivalent inertia constant.	Enables online estimation; suitable for systems with heterogeneous components. Accuracy may degrade when the damping coefficient D is small. Proven effective in moderate system sizes such as the IEEE 36-bus system.
[57]	Applies a small perturbation signal by modulating active power using any device capable of injecting or absorbing power. Frequency deviations are measured using GPS-synchronized extensible measurement units (XMUs), and inertia is estimated using the swing equation and measured RoCoF.	Utilises low power perturbation signal. Requires multiple XMUs and GPS synchronization; includes estimation delay due to 1-h averaging. Proven effective in an islanded Japanese grid with 5 diesel generators.
[58]	Introduces small step perturbations through an energy storage system (ESS).	Straightforward method. Offline process; sensitive to signal filtering and preprocessing. Proven effective on a 3.125 MVA diesel genset and an experimental 13 kW natural gas genset.
[59]	Evaluates four different types of small perturbation signals and uses a moving horizon estimation (MHE) algorithm based on local frequency and ROCOF measurements to estimate inertia and damping constants.	Supports real-time estimation using only local measurements; The study proves that using square wave excitation yields the highest estimation accuracy. Performance is highly sensitive to signal design (amplitude, ramp rate, crest factor). Proven effective in a PV–Hydro–ESS microgrid.
[60]	Injects small perturbation signals through a grid-forming converter. The virtual rotor speed is measured and fitted using vector fitting (VF) to extract the principal frequency dynamics and estimate system inertia.	Does not require generator-level models or measurements. Requires a controllable grid-forming converter and assumes high SNR. Proven effective in modified IEEE 39-bus and IEEE 118-bus systems.

3.4. Model-assisted identification methods

Model-assisted identification methods refer to techniques that rely on simplified or reduced-order dynamic models to estimate system parameters, typically using real-time measurement data. Unlike purely data-driven approaches, these methods incorporate prior structural knowledge of the system. These methods can be classified as follows.

a **Micro-Perturbation-Based Estimation Methods (MPM)**

These methods are particularly well-suited for modern power systems composed of components with diverse and nonlinear dynamic behaviours, such as renewable energy sources, energy storage systems, electric vehicles, and DC grids [56]. These typically employ a first-order transfer function to model the relationship between active power output deviations and angular speed, with system inertia treated as an unknown parameter within the transfer function. Unlike traditional swing-equation-based methods, MPM does not rely on large disturbances to identify system parameters. Instead, a small perturbation signal is deliberately introduced into the system to induce variations in frequency and active power at the point of common coupling. The system response to this perturbation signal, specifically, deviations in frequency and active power, is carefully measured. These measurements are then used to fit the transfer function and accurately identify its unknown parameters, including system inertia [6]. Table VIII summarises various perturbation-based methods in the literature, each differing in perturbation signal design and implementation complexity.

In summary, micro-perturbation-based estimation methods offer a flexible and effective framework for inertia estimation in low-inertia and heterogeneous power systems. Their key advantage lies in their ability to perform parameter identification without relying on large disturbances, making them suitable for real-time and online applications. They are especially compatible with systems hosting inverter-based resources and fast-acting devices. However, these methods generally require careful design of the perturbation signal to ensure sufficient excitation and a favourable signal-to-noise ratio. In addition, some formulations depend on high-accuracy measurement infrastructure, such as PMUs and may exhibit sensitivity to preprocessing, filtering, or signal tuning.

b **Kalman Filter-Based Estimation Methods**

Kalman filter, and its variation, the extended Kalman filter (EKF), are other model assisted-identification methods [6]. These methods notably excels in environments with high levels of noise. They function by iteratively refining estimates of system states and parameters, such as inertia, based on newly acquired measured data [61]. Various methods in literature use the Kalman filter for inertia estimation, which are summarized in Table IX.

In summary, the Kalman filter-based methods operates in real time. However, these methods assume that the system model is known (the equations describing the system dynamics). Therefore, if the model is incorrect or incomplete, this can lead to inaccurate estimates. Additionally, for non-linear systems, the process of linearization can introduce errors.

Table 9
Summary of Kalman-based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[62]	Uses a robust Kalman filter with PMU data	Resilience to uncertainties. Dependency on high-quality synchrophasor measurements can be a limitation. Proven effective in moderate system sizes such as IEEE 39-bus system.
[63]	Employs an extended Kalman filter for inertia and rotor angle estimation	Reduces the estimation error when the exact time of disturbance is known. Prone to errors if the disturbance timing is incorrect. Accuracy varies with the initial assumption of inertia constants, showing a potential error range from −90 % to +100 %. Proven effective in small microgrids.
[31, 64]	Applies both EKF and unscented Kalman filter (UKF) for inertia estimation	UKF provides higher order state estimation compared to EKF, which improves accuracy in highly nonlinear systems. UKF requires more computational resources compared to EKF. Proven effective in small models such as a single-machine-infinite-bus model.
[65]	Two-stage Kalman filter for power system state and inertia estimation	Enhances real-time responsiveness to dynamic state changes, crucial for power systems with high renewable penetration. Complex and reliance on accurate initial system modelling and noise characteristics. Proven effective in small modern systems.
[66]	Applies UKF for adaptive inertia estimation	Provides robust and fast parameter estimation suitable for real-time adaptive protection systems. Complexity increases with the scale of the power system. Proven effective in moderate system sizes such as IEEE 16-machine 68-bus system model.
[67]	Dynamic state and parameter estimation using EKF with PMU data	Implements EKF for estimation of rotor angle and inertia. Reduces computational load. Dependent on the quality and availability of PMU data, which can be a limitation. Proven effective in small system such as 9-bus system.

3.5. Machine learning and AI-based estimation methods

These methods are particularly effective for real-time inertia estimation in systems with a high penetration of RESs. Instead of relying on predefined system models or significant disturbance, they utilise the minor fluctuations in the power system, such as variations in power output from renewable sources, to deliver accurate inertia measurements [68]. The effectiveness of machine learning (ML)–based inertia estimation methods is heavily dependent on the quality and diversity of the training dataset. Machine learning models are commonly trained on ambient or small-signal operating data, rather than rare, large-scale disturbances. This reliance on ambient data improves real-world applicability, especially as modern power systems increasingly utilise high-resolution, time-synchronized measurements from advanced digital devices. The continued development of measurement infrastructure, including cloud-based storage and wide-area monitoring systems, will make such diverse datasets more accessible, thereby enhancing the performance and scalability of ML approaches in future grids. Furthermore, the inherent risk of overfitting in ML models can be effectively mitigated through standard regularization strategies, such as dropout, early stopping, batch normalization, and cross-validation. Together, these advances position ML-based methods as a promising and practical tool for real-time inertia estimation in increasingly complex and dynamic power systems. The ML-based methods can be sub-classified as follows [69].

- *Artificial Intelligence-Based Estimation Method*

AI-based estimation methods, including artificial neural networks (ANN), are machine learning-based estimation methods and excel in addressing the complexities of modern power systems, even in low-inertia systems [70]. These methods use historical data from PMUs to estimate system inertia and disturbance size. They rely on measurements such as the total active power generated by all generators and the frequencies at different buses [71]. Various methods in literature use AI which are summarized in Table X.

In summary, the adoption of AI-based methods underscores their capability for more accurate and real-time inertia estimation. Nonetheless, these methods come with their own set of challenges, such as the need for extensive datasets for model training, the possibility of overfitting, and the "black box" nature of ANN models. They require significant computational power and specialised knowledge for effective implementation. They are sensitive to significant noise in the training data, which can adversely affect the accuracy.

- *SINDy-Based Estimation Method*

Table 10
Summary of AI-based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[68]	Utilises long-recurrent convolutional neural network (LRCN) and graph convolutional neural network (GCN) for inertia estimation. Uses 1100 samples from ambient probing for training and validation.	Achieves high estimation accuracy of 97.34 % for LRCN and 98.15 % for GCN. Dependence on the quality of PMU data for training and operation. Proven effective in moderate system sizes such as IEEE 24-bus system.
[71]	Employs ANN-based models for inertia forecasting. Uses between 80 and 160 steady-state operating points for training and validation.	Provides robust inertia forecasts in renewable-intensive power systems. Dependent on the availability and granularity of input data from wind farms. Proven effective in small power system consists of multiple wind farms.
[72]	Integrates ANN-based approach. Uses 81,744 samples from ambient probing for training and validation.	Utilises HVDC converter-triggered perturbations for system inertia estimation. Offers robustness to noise with 96.4 % accuracy. Depends on the quality of input data for high accuracy. Proven effective in moderate system sizes such as IEEE 39-bus system.
[73]	Utilises convolutional neural networks (CNN) for continuous inertia estimation. Uses 300,000 s of ambient simulation data for training and validation.	Provides real-time inertia tracking, crucial for adaptive grid management. Requires extensive data and resources for training. Proven effective in moderate system sizes.
[74]	Utilises CNN with local frequency measurements. Uses 1700 samples from ambient probing for training and validation.	Provides accurate inertia constant estimates with 97.35 % accuracy. Relies on the presence and accuracy of local measurement systems and their integration with CNNs. Proven effective in moderate system sizes such as IEEE 39-bus system.
[75]	Residual neural network (ResNet) for inertia estimation in low-inertia systems. Uses 2951 samples from disturbance-based events.	Enhances estimation accuracy (97.8 %) through deep learning. Relies heavily on accurate and comprehensive training data (limitation in real-world operational conditions). Proven effective in moderate system sizes such as IEEE 39-bus system.

The SINDy (sparse identification of nonlinear dynamics) method is another machine learning-based method commonly employed when the governing equations of the power system are unknown [76]. This method is also useful in systems where traditional models may fall short in capturing intricate relationships in complex power systems. Fig. 6

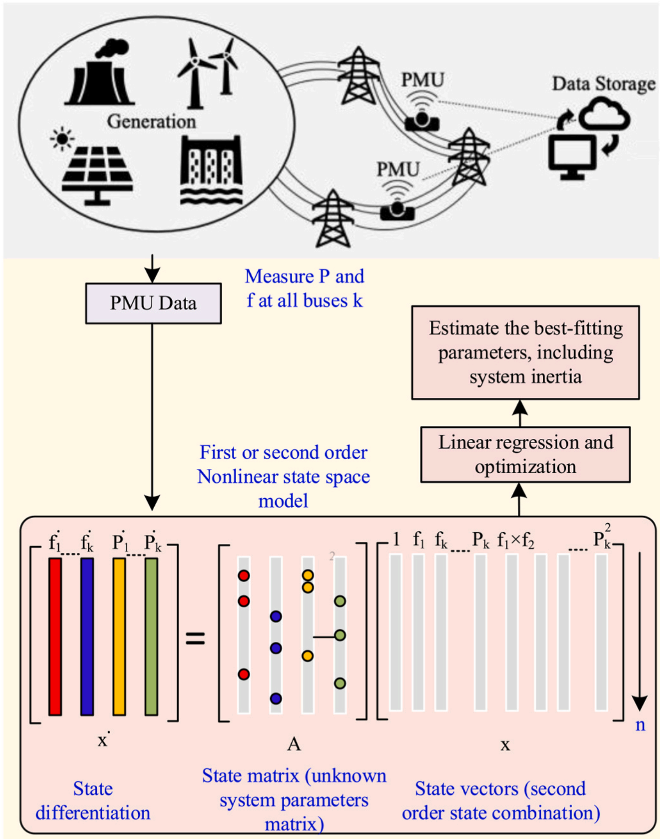

Fig. 6. SINDy method for inertia estimation.

shows the operational framework of the SINDy method. The method initiates by recording key system measurements such as frequency and active power from all buses (k) over a specific period (n). These measurements are considered as states of the system, which capture its dynamic behaviour. A nonlinear state-space model, typically based on a second-order nonlinear relationship, is assumed using these states for inertia estimation. This nonlinear state space model comprises state differentiation vectors, the state vectors, and the state matrix. State differentiation vectors are constructed by applying numerical differentiation to the measured states over the time period (n). On the other hand, the state vector includes the measured states from all buses (k), and their second-order combinations, such as the product of a state with itself and the cross-product of different states. An unknown parameter matrix, including inertia, is assumed to correlate the state vectors and their derivatives vectors. The method then employs iterative refinement of this parameter matrix through linear regression, that aims to minimize the prediction error against the nonlinear model assumptions. This iterative process enhances the accuracy of the estimated parameters, which ensures they closely represent the dynamics of the grid. Various methods in the literature employ SINDy for parameter identification, which are summarized in Table XI.

In summary, the primary advantage of this method is its capability to estimate system inertia in scenarios where there is a lack of precise knowledge about the governing differential equations, which is typical in complex systems. However, a potential disadvantage of the SINDy method is the necessity for a substantial amount of precise data to achieve accurate estimation along with its high computational time.

3.6. *Frequency domain-based estimation methods*

These methods operate in the frequency domain, in contrast to the previous methods that estimate directly in the time domain. These methods utilise transformations such as the Fourier transform or Wavelet transform to analyse system frequency responses to disturbances in the frequency domain, which are then used to estimate inertia [6,9]. These methods are classified based on the transformer used, as follows.

Table 11
Summary of SINDy based inertia estimation methods.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[77]	Utilises EKF and SINDy methods	Enables precise and real-time estimation of system dynamics, ideal for developing predictive digital twins. Relies on the precision and availability of data. Proven effective in small and simple models.
[78]	Utilises SINDy method for parameter identification	Achieves high accuracy in parameter estimation and enhances the precision of dynamic power grid models. Dependent on the quality and granularity of time-series data. Proven effective in moderate system sizes such as IEEE 39-bus system.
[79]	Utilises SINDy and performs a comparison with Physics-informed neural networks (PINNs)	Achieves high accuracy in dynamic modelling across various system conditions with notable computational efficiency. Relies on detailed and high-quality data. Effective in moderate and small sizes such as 6 and 39 bus systems.
[80]	Comparative analysis of SINDy and sliding window Methods	Identifies that the SINDy algorithm is not suitable for real-time applications compared to the sliding window algorithm, which demonstrates higher precision and more manageable computational complexity. Effective in small system sizes such as 11-bus system.

- *Wavelet-Based Estimation Method*

The wavelet-based method is a precise frequency domain-based estimation method [81]. Wavelet transforms offer both time and frequency information for the measured signal, which makes it effective for the precise localization of transients [82]. This method is particularly useful in systems where the frequency response is relatively dynamic over the period of interest. However, the effectiveness of the Wavelet-based method heavily depends on the quality of digital sampling; inaccurate or insufficient sampling can lead to error in inertia estimates. Moreover, the Wavelet transform is computationally intensive, particularly in large systems with complex oscillation modes [83].

- *Discrete Fourier Transform (DFT)-Based Estimation Method*

The DFT-based method is another frequency domain-based estimation method. Unlike wavelet estimation, this method is particularly useful in systems where the frequency response is relatively stationary over the period of interest [84]. DFT-based methods can be sensitive to noise, which can compromise the accuracy and reliability of the results. Additionally, DFT may struggle to capture short-term, non-stationary oscillations in systems that are strongly damped, and in large-scale systems with multiple oscillation modes, the computational demands increase [85]. A limited number of references utilise the DFT and wavelet for inertia estimation, which are summarized in Table XII.

4. Comprehensive evaluation of inertia estimation methods

This section presents an in-depth evaluation of inertia estimation methods, structured into three key dimensions, which are described in Fig. 7. The first part evaluates the methods based on critical performance

Table 12
Summary of DFT and wavelet-based methods in literature.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[86]	Wavelet-based adaptive algorithm for power disturbance analysis	Increases accuracy in the analysis of power flows, especially under conditions of low inertia and high renewable penetration. Complexity and computational demands may limit deployment in larger microgrids. Proven effective in small microgrids.
[87]	Combines interpolated DFT and Kalman filtering	Achieves lower estimation errors and suitable for dynamic grid environments. Complex implementation and dependent on precise model tuning. Proven effective in moderate system sizes such as IEEE 16-machine 68-bus system model.
[88]	Enhanced DFT-based estimation of dynamically time-varying inertia	Provides high accuracy and reduced computational load. Implementation complexity due to the need for precise model tuning and signal separation. Proven effective in small models such as small motors or generators.

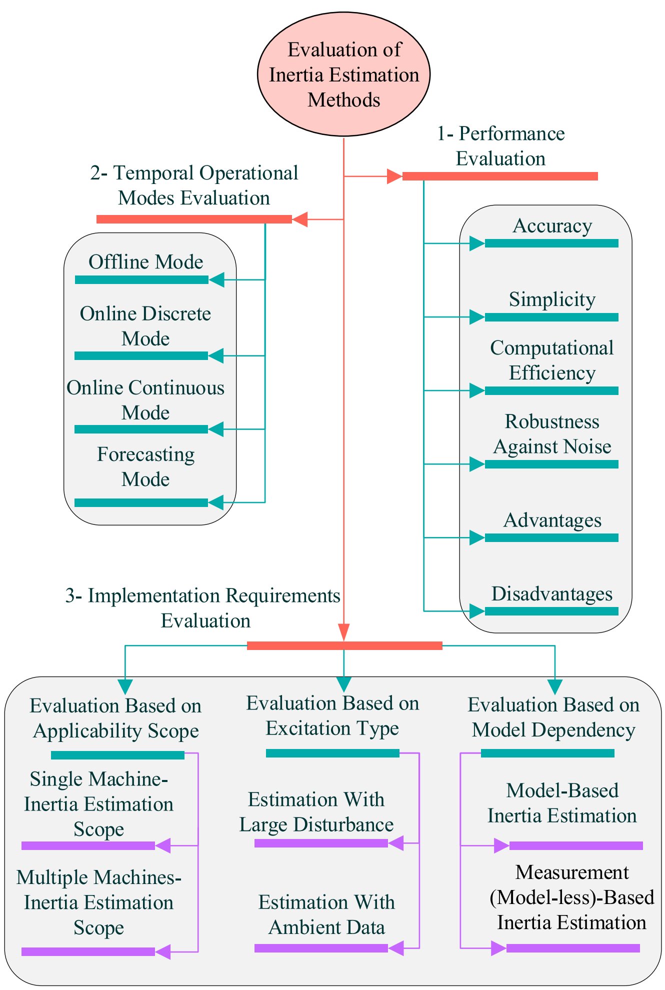

Fig. 7. Comprehensive evaluation of inertia estimation methods.

metrics such as accuracy, simplicity, computational efficiency, and robustness against noise, while also highlighting the advantages and disadvantages of each method. The second part evaluates the capability of each method to operate in different temporal operational modes and offers insights into their suitability for offline, online discrete, online continuous, and forecasting operations. The third part evaluates the methods based on their implementation requirements. The variation in these requirements is significant, as some methods depend on pre-defined mathematical models for functionality, while others rely on direct measurements to acquire system inertia information. Additionally, while some methods are specifically designed for single-machine applications, others can be adapted to estimate the equivalent inertia of multiple machines. While certain methods require significant disturbances to function effectively, others can utilise ambient data to accurately assess inertia under normal conditions without major disturbances. Therefore, each method has specific implementation requirements that can either enhance its performance in certain environments or limit its capabilities in others.

4.1. *Performance evaluation of inertia estimation methods*

Inertia estimation methods differ significantly in their performance when evaluated against key metrics such as accuracy, simplicity, computational efficiency, and robustness against noise. Each method presents specific advantages and disadvantages, which influence its applicability in different environments, particularly in low-inertia power systems. Table XIII summarises these key metrics for the inertia estimation methods.

4.2. *Evaluation based on temporal operational modes*

Each inertia estimation method is designed to operate within specific temporal operational modes based on its capabilities and intended application. These modes can be broadly categorised into offline, online discrete, online continuous, and forecasting. This section will describe each temporal operational mode in detail and define which inertia estimation methods are most suitable for each mode.

a **Offline Inertia Estimation Mode**

Offline inertia estimation is typically performed post-event, where system dynamics are analysed after major disturbances, such as generator outages or significant changes in load. This mode uses historical data to calculate total system inertia [24]. It typically requires low computational effort. However, as with any post-event analysis, offline mode is limited to specific time periods after disturbances, which makes it unsuitable for real-time monitoring or proactive grid management. The accuracy of offline estimation mode can be affected by factors such as the size of the disturbance, measurement noise, and oscillations in the system, which can distort the RoCoF calculations. Therefore, methods such as polynomial fitting, and low-pass filtering are typically employed to enhance the reliability of RoCoF calculations. Another significant disadvantage is that the offline estimation mode becomes increasingly challenging with the higher penetration of RESs.

The most suitable methods for offline estimation mode include swing equation-based methods, modified swing equation-based method, second derivative of frequency-based method, frequency domain-based methods, and R, V, and RV-based methods. Fig. 8 summarises the most suitable methods for each temporal operational mode.

b. **Online Discrete Inertia Estimation Mode**

Online discrete inertia estimation mode typically uses PMU data to provide near real-time estimates of system inertia. This mode focuses on capturing system-wide events such as generator trips or large load variations, which cause noticeable frequency deviations. The primary advantage of this mode is its ability to estimate inertia in near real-time, which allows grid operators to react swiftly to disturbances. However, online discrete mode faces several challenges, such as its limited resolution, as it only provides estimates during specific events and lacks the continuity offered by online continuous mode. Additionally, it highly

Table 13
Summary of key performance metrics of inertia estimation methods.

Estimation Method	Concept	Accuracy	Simplicity	Computational Efficiency	Robustness Against Noise	Advantages	Disadvantages
Swing Equation-Based Methods	Utilises the relationship between system frequency and power imbalance	Low to moderate (≈80 %–85 %)	High (requires only power and frequency measurements)	High (milliseconds to seconds)	Moderate	Simple, and widely recognized	Overlook complex actual dynamics, and numerical challenges
Modified Swing Equation-Based Method	Refines the swing equation with advanced dynamics for improved estimation	Moderate (≈85 %–90 %)	Moderate to high (includes complex power system dynamics)	Moderate to high (seconds to tens of seconds)	Moderate to high	Enhances numerical stability	Optimal parameter selection increases computational needs and impacts adaptability in different environments
Second Derivative of Frequency (SDFD)-Based Method	Inertia estimation using the acceleration of frequency changes	Moderate (≈85 %–90 %)	Moderate to high (intensive filtering required and IPD algorithm)	Moderate to high (seconds to tens of seconds)	Low to moderate	Robust, and model independence	Uncertainties with noisy data, and demands high precise measurements
Sliding Window-Based Method	Utilises a sliding window of measurements rather than relying on a single measurement	Moderate (≈85 %–90 %)	Moderate to high (requires filtering sliding windows)	Moderate to high (seconds to tens of seconds)	High	Allows for localized analysis, and adepts with transient events	Critical window size selection, and potential overlook of long-term responses
R, V, and RV-Based Methods	Improved Inertia estimation from frequency deviation or voltage magnitude changes post-disturbance	Moderate to high (≈85 %–95 %)	Moderate (requires accurate measurements and includes the non-linear load dynamics)	Moderate to high (seconds to tens of seconds)	Moderate to high	Accounts for load dependency on frequency and voltage	Challenge in defining load and frequency/ voltage correlation
Stochastic Model-Based Method	Applies stochastic models to measurements for inertia variation capture	Moderate to high (≈85 %–95 %)	Low (extensive data requirement)	Low (tens of seconds to minutes)	Low to moderate	Capable of real-time estimation, and handles system complexity	Data quality dependency, requires advanced statistical knowledge, and complex
ARMAX Model-Based Method	Utilises auto regression, moving averages, and exogenous inputs for inertia estimation	High (≈90 %–95 %)	Low to moderate (detailed parameter and complex model selection for fitting)	Low (tens of seconds to minutes)	Moderate to high	Comprehensive dynamics modelling, and includes external influences	Extensive data requirement, computationally intensive, and model order selection is critical
Micro-Perturbation-Based Method (MPM)	Online inertia estimation in normal operation based on minor perturbations	Low to moderate (≈80 %–85 %)	Moderate (intensive measurements required)	Moderate to high (seconds to tens of seconds)	Moderate	Suitable for micro disturbance-based online estimation	Requires perturbing the system, which may not be practical
Kalman Filter-Based Methods	Uses real-time measurements with predictive updates for system state and parameters estimation	High (≈90 %–95 %)	Low to moderate (requires accurate model system dynamics)	Moderate to high (seconds to tens of seconds)	High	Real-time estimations with predictions, and offers dynamic updating	High computational demand, complex, and accuracy is dependent on the assumed model
Machine Learning-Based Methods	Utilises historical data patterns and machine learning for inertia estimation	High (≈90 %–95 %)	Low to moderate (training data quality significantly need time and storage)	High during estimation (milliseconds to seconds), low during training	High	Adaptive, flexible, and capable of learning from large datasets	Dependence on data quality, and risks of model overfitting
Frequency Domain-Based Methods (Wavelet and DFT)	Analyses system oscillations using discrete Fourier transform or Wavelet transform for inertia estimation	Low to moderate (≈80 %–85 %)	Low (frequency-domain analysis requires computation resources)	Low (tens of seconds to minutes)	Low to moderate	Efficient in oscillations analysis, and no derivative calculations needed	Large-system complexity, and noise sensitivity

affects by system noise, particularly in systems with high levels of renewable generation. To enhance the accuracy of online discrete mode, methods such as Kalman filter-based methods and ARMAX model-based method are often employed. These methods help to filter out noise and provide more reliable estimates.

The most suitable methods for online discrete mode include swing equation-based methods, modified swing equation-based method, second derivative of frequency-based method, R, V, and RV-based methods, Kalman filter-based methods, ARMAX model-based method, and frequency domain-based methods.

c. **Online Continuous Inertia Estimation Mode**

Online continuous inertia estimation provides real-time, continuous monitoring of system inertia using PMU data or wide area measurement systems (WAMS). This mode offers the highest temporal estimation resolution, which makes it suitable for real-time applications in systems with high RES penetration. Unlike online discrete mode, which provides estimates only during specific disturbances, online continuous mode maintains a constant flow of estimates under both disturbed and normal conditions. This continuous monitoring allows grid operators to track inertia fluctuations in real time and proactively manage changes in system stability. However, several challenges are associated with online continuous mode. One of the primary difficulties lies in the accurate estimation of power imbalances during normal operations, where disturbances may be small and difficult to detect. Additionally, the computational complexity of continuous estimation is higher than that of discrete mode. Noise and electromechanical oscillations can also

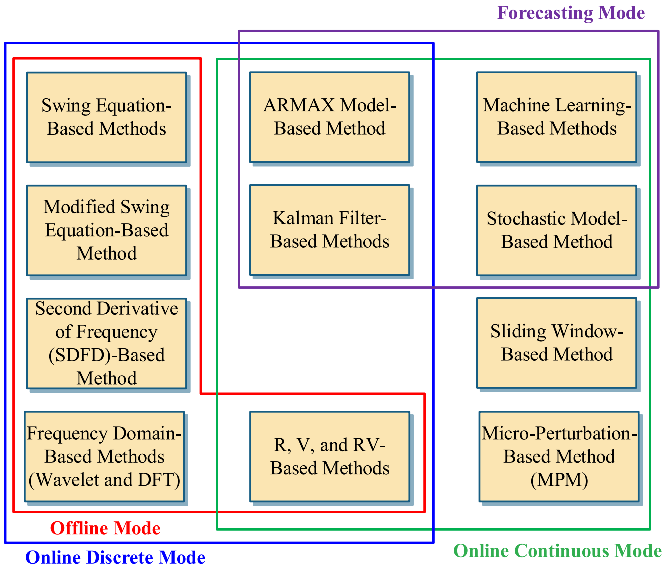

Fig. 8. Suitable inertia estimation methods for different temporal operational modes.

affect the accuracy of inertia estimates, which requires the application of filtering and signal processing techniques.

The most suitable methods for online continuous mode include ARMAX model-based method, Kalman filter-based methods, R, V, and RV-based methods, machine learning-based methods, stochastic model-based method, sliding window-based method, and micro-perturbation-based method.

d. **Forecasting Inertia Estimation Mode**

Forecasting inertia estimation predicts future system inertia based on generator schedules, renewable energy forecasts, and demand forecasts. This mode is particularly useful for operational planning and risk management, which allows system operators to predict changes in inertia and take pre-emptive actions to mitigate frequency stability issues. Forecasting is critical in low-inertia systems, where the variability of renewable energy sources can lead to significant fluctuations in system inertia. Forecasting mode faces several key challenges, such as the accuracy of forecasts depends heavily on the quality of input schedules and forecasts. Additionally, system variability can introduce considerable uncertainty into forecasts.

The most suitable methods for forecasting mode include Kalman filter-based methods, ARMAX model-based method, machine learning-based methods, and stochastic model-based method. Table XIV summarises the comparative analysis of the temporal operational modes.

4.3. Evaluation of inertia estimation methods based on implementation requirements: model dependency, estimation excitation and applicability scope

Inertia estimation methods can be systematically evaluated by examining their underlying implementation requirements. These requirements are best understood by considering three fundamental factors: model dependency, excitation type, and applicability scope. Model dependency refers to the degree to which an estimation method relies on predefined mathematical models or prior knowledge of system dynamics. Excitation type pertains to the type of input signal or system condition used to initiate the estimation process. Applicability scope defines the spatial or operational level at which the method is intended to function, ranging from single-generator estimation to system-level inertia evaluation involving multiple generating units.

a. **Evaluation Based on Model Dependency**

The first factor related to implementation requirements focuses on the modelling demands inherent to each method. Specifically, it examines whether a method relies on explicit physical models of system dynamics with minimal dependence on measurements, whether it can operate primarily using measured data with minimal or no prior modelling information.

- *Model-Based Inertia Estimation*

Model-based inertia estimation primarily requires established mathematical models that represent the dynamic behaviour of power system components. Inertia estimation is then carried out by identifying unknown model parameters, through direct substation, optimization or filtering techniques. These methods rely on a minimal set of observed measurements, most commonly frequency and active power [8]. Common model-based inertia estimation methods include swing equation-based approaches, Kalman filter and its variants. When accurate system models are available, model-based methods can deliver high-fidelity inertia estimates. However, their performance is highly sensitive to modelling errors, parameter uncertainties, and unaccounted-for system dynamics. These limitations are especially significant in systems with a high proportion of converter-interfaced generation, where traditional modelling assumptions may no longer be valid.

- *Measurement (Model-less)-Based Inertia Estimation*

Measurement-based inertia estimation, also known as model-less, does not primarily require detailed mathematical dynamic models of power system components. Instead, these methods infer inertial characteristics directly from high-resolution, time-synchronized

Table 14
Comparative analysis of offline, online discrete, online continuous, and forecasting inertia estimation modes in power system.

	Offline Mode	Online Discrete Mode	Online Continuous Mode	Forecasting Mode
Concept	Utilises post-disturbance data to calculate system inertia	Estimates inertia from PMU data during disturbances	Estimates inertia from PMU or WAMS data continuously during disturbances and normal operations	Predicts system inertia based on generator schedules, renewable energy and demand forecasts
Advantages	Simple and computationally efficient	Provides near real-time estimates, high accuracy, and applicable for wide range of disturbance levels	High temporal estimation resolution (typically updates every 0.1–1 s), suitable for real-time control, and enhanced accuracy	Aids in operational planning, critical for decision-making, and adjustable forecasting horizons align with service markets
Limitations	Relies on disturbance size knowledge, limited to retrospective analysis, and less effective with low inertia systems	Limited temporal resolution (updates only during disturbances), estimation accuracy dependent on precise disturbance detection, and faces difficulties with real-time processing	High computation time, complex, requires advanced data processing capabilities and filtering process	Limited by the availability of schedule and the historical data, and time-series models used in forecasting are complex and significantly influence accuracy

measurements. In addition, these methods require the use of signal processing techniques, statistical analysis, or machine learning algorithms to extract inertia-related features from the measured system response. Common measurement-based inertia estimation methods include stochastic dynamic methods, and machine learning methods. These methods provide increased flexibility where system models are incomplete, complex or unavailable. However, their accuracy and reliability can be limited by the quality of measurement data, sensitivity to noise, and the challenge of distinguishing inertia-related dynamics from other control actions, such as primary frequency control.

b. **Evaluation Based on Excitation Type**

The second factor related to implementation requirements focuses on the nature of the excitation signal used to initiate the inertia estimation process. This factor distinguishes between methods that require large disturbances, such as generator trips or sudden load changes, and those that operate under ambient conditions using small-signal variations naturally present in the system.

- *Large Disturbance-Based Inertia Estimation*

Large disturbance-based inertia estimation utilise the system frequency response following major events such as generator outages, or load shedding. This approach typically analyses the RoCoF during the initial inertial response period, before the activation of primary frequency control mechanisms. Accurate estimation in this context requires high-resolution frequency measurements, along with a reliable assessment of the power imbalance caused by the disturbance. Both model-based and measurement-based estimation methods can be used to estimate system inertia following such large disturbances.

- *Ambient Data-Based Inertia Estimation*

Inertia can be estimated using ambient data, which capture the natural fluctuations in signals such as frequency caused by random small load variations or inherent variability in renewable generation. This approach enables continuous inertia estimation and is particularly advantageous in modern low inertia power systems, where large disturbances are either uncommon or undesirable. However, ambient based methods may be susceptible to noise and measurement uncertainty, particularly in low signal-to-noise environments, unless advanced filtering and signal processing techniques are employed to extract meaningful dynamic information. Table XV provide a comparative analysis between large disturbance-based and ambient data-based inertia estimation.

c **Evaluation Based on Applicability Scope**

The third factor related to implementation requirements focuses on the scope of applicability. This includes whether the method targets a single synchronous machine or aims to provide inertia estimates at an aggregated system or regional level.

- *Single Machine Inertia Estimation Scope*

This scope is typically applied to estimate the inertia of a single machine, such as a SG or a non-synchronous converter [63,67,89–99]. Methods designed for this specific scope are generally implemented using local measurements obtained directly from the machine terminals. The most suitable methods for this purpose include swing equation-based methods, modified swing equation methods, second derivative of frequency-based methods, and Kalman filter-based estimators. Despite their effectiveness for individual machine-level analysis, the localized nature of these methods limits their applicability in evaluating system-wide inertia. Furthermore, their performance depends heavily on the accuracy of local measurements.

Table 15
Comparative analysis between large disturbance-based and ambient data-based inertia estimation.

	Large Disturbance-Based Estimation	Ambient Data-Based Estimation
Required Data Inputs	RoCoF calculations during disturbances and sometimes power imbalance	Continuous flow of ambient data from different measurement devices during disturbances and normal operations
Sensitivity to Renewable Integration	Moderate to high (varies with disturbance magnitude and how the renewable sources affect the RoCoF response)	Low to moderate (depend on the size and accuracy of the data)
Advantages	Rapid results, and suitable for real-time disturbance analysis	Commonly model-free, continuous monitoring of inertia, and suitable for normal operation
Disadvantages	Requires significant disturbances, challenges in estimating RoCoF accurately, and typically uses terminal frequency as a proxy for machine rotor speed	Requires extensive data for reliable estimation, and highly sensitive to noise and data quality

- *Multiple Machines Inertia Estimation Scope (Regional Inertia Estimation)*

In large-interconnected power systems, it is often necessary to estimate the inertia of an entire region or a group of machines. If a model-based approach is adopted for this scope, equivalent system models are constructed by aggregating coherent generators and their associated loads. This enables the estimation of regional inertia through reduced-order dynamic equivalents that represent the collective behaviour of the subsystem. Alternatively, if a measurement-based approach is adopted for this scope, PMU data collected at inter-area boundaries. These measurements are then used to infer the net inertia contribution of the region [100–108]. The most suitable methods for this scope include the Kalman filter-based method, the ARMAX model-based method, and the machine learning-based methods. While regional methods offer broader coverage and system-level insights, they introduce their own challenges. These include managing heterogeneous generation mixes (including both SGs and CIGs) as well as managing and synchronizing measurements collected across wide geographical areas. Fig. 9 illustrates the applicability scope of inertia estimation methods, with Fig. 9(a) depicting the estimation for a single machine and Fig. 9(b) representing the estimation across multiple machines.

Table XVI provides an evaluation of inertia estimation methods

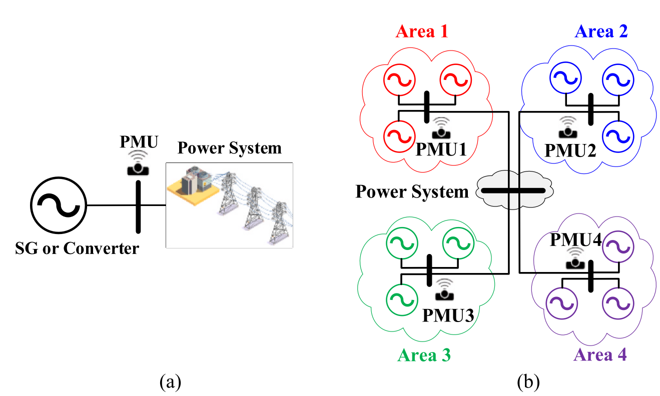

Fig. 9. Applicability scope of inertia estimation methods, (a) inertia estimation for a single machine, and (b) inertia estimation for multiple machines.

Table 16
Evaluation of inertia estimation methods based on model dependency and applicability scope.

Estimation Method	Model Dependency	Excitation Type	Estimation Scope
Swing Equation-Based Methods	Model-based (classical swing equation)	Typically applied following large disturbances	Single machine or regional
Modified Swing Equation-Based Method	Model-based (classical swing equation with damping constant)	Typically applied following large disturbances	Typically used with single machine in literature
Second Derivative of Frequency (SDFD)-Based Method	Model-based (derivative of the classical swing equation)	Typically applied following large disturbances	Single machine or regional
Sliding Window-Based Method	Measurement-based (uses simple division between average power and RoCoF)	Typically applied following large or ambient fluctuations	Single machine or regional
R, V, and RV-Based Methods	Measurement-based (relies on empirical relationships between RoCoF, voltage, and power changes)	Typically applied following large disturbances	Typically used for regional-level estimation.
Stochastic Model-Based Method	Measurement-based (relies on self-generated stochastic models such as Markov models)	Typically applied under normal operating conditions	Typically used for regional-level estimation.
ARMAX Model-Based Method	Measurement-based (relies on self-generated ARMAX model without physical modelling)	Typically applied under ambient conditions or small-disturbance.	Single machine or regional
Micro-Perturbation-Based Method (MPM)	Measurement-based (typically assume a simple first-order transfer function model)	Typically applied following controlled probing signals	Typically used with single machine
Kalman Filter-Based Methods	Model-based (full or reduced state-space models)	It can be applied under ambient conditions or disturbances.	Single machine or regional
Machine Learning-Based Methods	Measurement-based	Typically applied under normal operating conditions	Typically used for regional-level estimation.
Frequency Domain-Based Methods (Wavelet and DFT)	Measurement-based	It can be applied under ambient conditions or large-disturbance.	Typically used with single machine

based on their commonly reported model dependency, excitation type and applicability scope, as documented in the existing literature.

5. AHP-based ranking and optimal environmental recommendations for inertia estimation methods

This section builds on the comprehensive evaluations conducted in the previous section and is divided into two parts. The first part ranks the estimation methods based on the key performance metrics, using an AHP-based approach, to determine the most suitable method in the low inertia power systems. The second part provides recommendations for the most suitable environments for each inertia estimation method in general.

5.1. *AHP-based ranking of estimation methods for low-inertia power systems*

The AHP-based approach ranks the estimation methods to identify the most suitable method for low-inertia power systems with high penetration of RESs. It uses the key performance metrics outlined in Table XIII, which include accuracy, simplicity, computational efficiency, and robustness against noise. Since the AHP process requires numerical values, the qualitative performance metrics scores (such as low, moderate, and high) from Table XIII are converted into quantitative scores. Each performance metric is assigned a score from 1 to 5, where 1 represents the lowest performance and 5 indicates superior performance. This scoring process is applied consistently across all methods and their metrics, as illustrated in Fig. 10. The AHP-based approach then assigns equal weights to each performance metric, with each metric given a weight of 25 %, reflecting their balanced importance in low-inertia systems with high penetration of renewable energies. Fig. 11 presents the final ranking of the methods based on these weighted scores. Machine learning-based methods, Kalman filter-based methods, and the sliding window-based method emerge as the top-ranked methods, particularly excelling in accuracy, real-time performance, and robustness to noise, which make them well-suited for systems with high renewable variability. In contrast, methods such as the frequency domain-based estimation methods rank lower, primarily due to their limitations in handling real-time demands and noise resilience, which are essential in modern renewable energy systems.

5.2. *Recommendations on suitable environments for inertia estimation methods*

This part builds on the comprehensive evaluations from Section IV, which considers key performance metrics, temporal operational modes, and implementation requirements of the estimation methods. Based on these evaluations, this part provides recommendations for the most suitable environment for each inertia estimation method. These recommendations take into account factors such as system scale (small, medium, or large), the type of power system (only synchronous generators or generation mix), and the operational mode (offline, online, or forecasting). Strengths and limitations of each method are matched to the most appropriate operational environments. The summary of environmental recommendations for each method is provided in Table XVII.

6. Special topics in inertia estimation: synthetic inertia estimation and electromechanical mode analysis

This section presents selected advanced topics in inertia estimation, highlighting recent developments in estimating synthetic and virtual inertia in inverter-based systems, as well as indirect estimation methods based on electromechanical mode analysis.

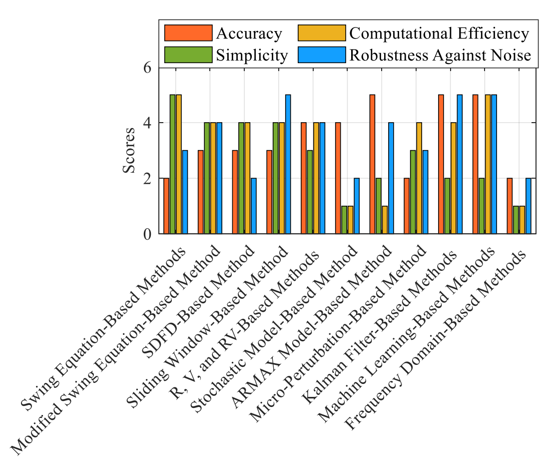

Fig. 10. Quantitative scoring of inertia estimation methods across key performance metrics.

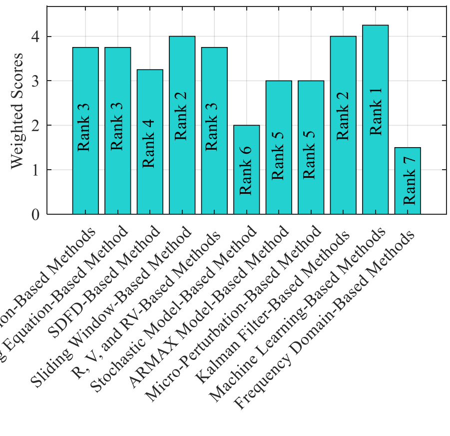

Fig. 11. Final ranking of estimation methods based on AHP weighted scores.

Table 17
Recommended environment for inertia estimation methods [6,11].

Method	Recommended Environment
Swing Equation-Based Methods	Small-scale systems, traditional synchronous generators, and offline or online estimation
Modified Swing Equation-Based Method	Small to medium-scale systems, generation mix, and offline or online estimation
Second Derivative of Frequency-Based Method	Small to medium-scale systems, traditional synchronous generators, and offline estimation
Sliding Window-Based Method	Small to medium-scale systems, generation mix, and online discrete estimation
R, V, and RV-Based Methods	Small to medium-scale systems, generation mix with highly variable loads and small renewable interfaces, and online or offline estimation
Stochastic Model-Based Method	Large-scale systems, generation mix with high renewable penetration, and online or forecasting estimation
ARMAX Model-Based Method	Medium to large-scale systems, generation mix, with renewable energy interfaces, and online or forecasting estimation
Micro-Perturbation-Based Method	Medium to large-scale, generation mix, and online estimation
Kalman Filter-Based Methods	Small to medium-scale systems, generation mix, and online estimation
Machine Learning-Based Methods	Large-scale systems, generation mix with complex dynamics, and online or forecasting estimation
Frequency Domain-Based Methods (Wavelet and DFT)	Small to medium-scale systems with periodic disturbances, generation mix, and offline estimation.

6.1. Estimation of synthetic (virtual) inertia in inverter-based power systems

This part reviews how the estimation methods classified in Section III have been adapted for application to synthetic inertia estimation. Particular attention is also given to advanced algorithmic frameworks that have been specifically developed to address the unique characteristics of synthetic inertia, including its fast dynamic response and time-varying behaviour. The summary of core contributions in synthetic and virtual inertia estimation methods is provided in Table XVIII.

6.2. Indirect inertia estimation using electromechanical modes analysis

Electromechanical mode-based methods estimate inertia by identifying the natural modes of oscillation in the system, specifically, their frequencies, damping ratios, and in some cases, mode shapes. These modes are extracted using system identification techniques such as autoregressive moving average (ARMA) modelling, matrix pencil (MP), or stochastic subspace identification (SSI). Once the modal parameters are

Table 18
Summary of core contributions in synthetic and virtual inertia estimation methods.

Category	Reference	Core contribution
Swing Equation-Based Methods	[109]	Proposed a discrete-time swing equation formulation using PMU measurements to estimate the equivalent virtual inertia of wind power plants.
	[110]	Incorporated internal reactance into swing equation-based estimation, enabling accurate aggregation of virtual inertia across multiple IBRs.
Sliding Window-Based Method	[111]	Developed an adaptive sliding time-window method combined with regression analysis to estimate equivalent inertia at the IBR-grid interface.
R-Based Method	[112]	Applied a R-based framework to support synthetic inertia control from energy storage systems.
ARMAX Model-Based Method	[113]	Employed a weighted recursive ARMAX model to identify system dynamics from frequency and power data, extracting system inertia from the step response.
	[114]	Proposed an online ARMAX-based estimator to quantify effective synthetic inertia and droop in VSC-HVDC systems.
Kalman Filter-Based Methods	[115]	Developed a UKF to estimate time-varying inertia and damping of grid-forming inverters using terminal measurements, considering current limiter effects.
	[116]	Designed an EKF enhanced by Grey Wolf Optimization to improve convergence and noise immunity in PMU-based virtual inertia estimation.
Micro-Perturbation-Based Method	[117]	Introduced a method using Hann-shaped perturbation signals injected by IBRs to excite system dynamics and estimate inertia and droop through linear regression.
Machine Learning-Based Methods	[118]	Trained a neural network on steady-state operational data to estimate system equivalent inertia, considering synchronous generators, asynchronous motors, and wind turbines with or without virtual inertia control.
Frequency Domain-Based Methods	[119]	Proposed a wavelet transform-based method to estimate virtual inertia by analysing frequency-domain characteristics of power and frequency signals.
Singular Value Decomposition + RoCoF Gradient Mapping	[120]	Presented a data-driven method using SVD and frequency gradient mapping on RoCoF to estimate time-dependent inertia with improved efficiency.
Advanced Systematic Classification algorithm	[121]	Developed a system identification-based method to classify and quantify non-synchronous inertia in AC microgrids through RoCoF and frequency deviation models.
Recursive Least-Squares Approach	[122]	Applied recursive least-squares estimation using electromechanical oscillation modes to estimate time-varying inertia in high-renewable systems.
Local Rational Model (LRM)	[123]	Proposed a non-parametric online estimation method using local rational models to track time-dependent virtual inertia without system model knowledge.
Impedance-Based Estimation	[124]	Developed an online estimation technique linking impedance and frequency response to determine nodal

(continued on next page)

Table 18 (*continued*)

Category	Reference	Core contribution
		inertia for both synchronous and inverter-based units.
Voltage-Controlled Zone Method	[125]	Introduced a voltage-controlled zone concept to separate and estimate load, synchronous, and non-synchronous inertia with minimal PMU data requirements.

identified, analytical relationships derived compute system or area-level inertia from these modes. In some cases, machine learning models are trained to map modal features to inertia values. Various methods in the literature employ electromechanical mode for inertia estimation, which are summarized in Table XIX.

7. Inertia estimation challenges and research directions

This section outlines the challenges and potential research directions related to inertia estimation in power systems. These challenges arise from the diversity of energy generators, and the growing complexity of recent power grids.

7.1. Challenges related to the influence of damping in inertia estimation

Inertia estimation methods often assume that damping effects are negligible immediately after a disturbance, as the system response is primarily driven by inertia during this initial period. This assumption is valid for traditional synchronous generators, where damping coefficients are low (1–3 pu) and have minimal impact on inertia estimation.

In contrast, RESs are connected to the grid through converters, such as grid forming converters, which have higher damping coefficients (20–30 pu). This high damping affects the system response immediately after a disturbance and makes accurate inertia estimation challenging when methods assume low damping. Future research should develop methods that consider both low and high damping scenarios. This will improve the accuracy of inertia estimation in systems with diverse generator types and high levels of renewable integration.

Table 19
Summary of electromechanical modes-based estimation methods in literature.

Ref.	Concept	Key advantage, disadvantage and test system characteristics
[126]	Estimates system inertia by matching the system electromechanical modes, obtained from frequency measurements using Prony method, with those of a linearised dynamic model.	Operates under ambient conditions. Requires accurate mode estimation, which is non-trivial for well-damped modes. Applied to IEEE 14 and IEEE 39-bus system and.
[106]	Estimates system equivalent inertia and damping coefficient by exploiting the analytical relationship between electromechanical oscillation parameters using local iterative filtering decomposition.	Requires only tie-line active power measurement. Estimation accuracy degrades under poor signal-to-noise ratio. Tested on two-area 4-generator system and IEEE 39-bus systems.
[127]	Combines rigid body and inter-generators modes for inertia estimation. It uses ARMA for modes extraction.	Uses multiple modes for improved accuracy and does not require knowledge of disturbance magnitude. High inertia weakens sensitivity of the rigid body mode to H. Validated on IEEE 14-bus and 39-bus systems.
[128]	Derives a mathematical relationship between inertia and electromechanical oscillation modes. It uses stochastic subspace identification or frequency decomposition for modes extraction.	Operates under ambient conditions, and high computational efficiency. Assumes ambient excitation is Gaussian and stationary. Only validated on single-generator infinite bus system.
[129]	Uses the modal parameters (frequency, damping, and mode shape) of inter-area oscillations and formulates the relationship between modal parameters and area-level inertia.	Enables area-level inertia estimation using only PMU data. Estimation accuracy may degrade in areas with weak coupling or high electrical distance. Validated on IEEE 16-generator and North China Grid.
[130]	Identifies electromechanical modes through the matrix pencil (MP) method, then clusters dominant modes using density-based spatial clustering of applications with noise, and finally employs a random forest regressor (RFR) to estimate the inertia constants per area	Robust to measurement noise. Requires prior training of the RFR model using historical data. Validated on 39-Bus New England system

7.2. Challenges related to the integration of hybrid data sources for inertia estimation

As renewable penetration increases, integrating multiple data sources for inertia estimation becomes necessary. Traditional inertia estimation relies heavily on PMUs and WAMS data; however, as grids become more complex, additional data sources, such as weather data, and IoT sensors from DERs, may enhance accuracy. A significant challenge lies in developing multi-source data fusion techniques that can combine these diverse datasets, each with different temporal resolutions and reliability levels, into a cohesive inertia estimation framework. Research into hybrid data integration and machine learning algorithms that can handle heterogeneous data sources would improve both the accuracy and responsiveness of inertia estimation.

7.3. Challenges in temporal decomposition of inertia

In systems with both fast-responding synthetic inertia and traditional synchronous inertia, separating the inertia response into different timeframes is a unique challenge. Synthetic inertia responds faster than mechanical inertia, which creates a need to estimate these components separately for effective control. Developing inertia estimation methods that distinguish between short-term synthetic inertia and longer-term synchronous inertia can improve control strategies. This approach allows for more precise tuning of grid parameters to balance both types of inertia in different operational scenarios.

7.4. Challenges related to inertia contribution of loads

As previously mentioned in the R, V, and RV-based estimation methods, the load does not remain invariably constant; it can be influenced by the voltage and frequency of the bus to which it is connected. For instance, synchronous motors are dynamic loads and inherently respond to frequency fluctuations in the power grid. Therefore, accurately assessing their contribution to inertia is challenging due to their diverse operational scenarios and widespread dispersion. Moreover, recent microgrids are experiencing changes in load types, notably due to the rise in data center power consumption and the expansion of loads powered by variable frequency drives, which significantly impact system dynamics. This trend highlights the need for research focused on precisely modelling, observing, and regulating the inertial contributions of these new types of loads to enhance inertia estimation accuracy.

Table XX summarises these key challenges in modern inertia estimation and highlights representative solutions proposed in the literature.

8. Conclusion

This paper provided a comprehensive review of inertia estimation methods, with a particular focus on their suitability in modern low-inertia power systems. The review has covered both traditional methods and cutting-edge estimation advancements. The estimation

Table 20
Mapping of key inertia estimation challenges to literature solutions.

Challenge	Reference	Proposed solution
Influence of Damping in Inertia Estimation	[8]	Reviews the impact of damping from converter-based resources and highlights methods capable of decoupling inertia and damping.
	[131]	Proposes an extended dynamic regression that jointly estimates inertia and damping.
	[132]	Uses an adaptive unscented Kalman filter to estimate time-varying inertia and damping.
	[117]	Employs probing signals to estimate inertia and droop as a damping proxy.
Integration of Hybrid Data Sources for Inertia Estimation	[69]	Combines synchrophasor, load, and weather data using machine learning for inertia estimation.
	[133]	Uses semi-parametric probabilistic models with hybrid data for day-ahead inertia forecasting.
	[134]	Proposes a real-time inertia estimation method using frequency and power data via dynamic regressor extension and mixing method, showcasing a scalable approach compatible with hybrid data integration.
Temporal Decomposition of Inertia	[117]	Uses Hann-window probing signals to distinguish synthetic and mechanical inertia.
	[135]	Evaluates the effect of different feedback signals on inertia response timing.
	[136]	Provides a framework for separating inertial and primary responses over time.
Inertia Contribution of Loads	[137]	Proposes a model that simultaneously estimates system inertia and load relief.
	[46]	Uses covariance analysis of ambient noise to estimate inertia including loads.
	[138]	Applies typicality-based data analysis to assess regional inertia, including motor loads.

methods were comprehensively categorised, characterised and evaluated based on their key performance metrics, temporal operational modes, and implementation requirements. The analytic hierarchy process-based ranking technique has been used to define the most suitable methods in low-inertia power systems with high penetration of RESs. The evaluation revealed that traditional methods, such as the swing equation, are often insufficient in systems with high levels of renewable energy penetration. In contrast, advanced methods including machine learning and Kalman filter-based methods, demonstrate greater adaptability in these environments. This review also underscored the importance of real-time and forecasting inertia estimation in maintaining grid stability and reliability. Methods such as sliding window, ARMAX models, and micro-perturbation-based estimations emerged as effective for continuous monitoring, whereas statistical and machine learning methods showed significant promise in predicting future grid conditions. Future research should focus on addressing unique challenges in inertia estimation, such as handling diverse damping scenarios, integrating hybrid data sources, and temporally decomposing synthetic and synchronous inertia.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mohamed Abouyehia reports financial support was provided by Energy Technology Partnership (ETP) and Scottish Power. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was funded by the Energy Technology Partnership (ETP) and Scottish Power.

Data availability

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

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