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A Revised Classification of Inertia Estimation Considering General and Time Horizon Perspectives

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***Abstract*— The increasing integration of renewable energy sources (RES) and the corresponding decline of synchronous generators (SGs) have significantly reduced power system inertia, posing challenges to frequency stability and grid resilience. Inertia estimation (IE) is essential for understanding system dynamics and enabling effective frequency control. This paper presents a revised classification framework for IE methods that considers two main dimensions: the general methodological approach (model-based vs. measurement-based) and the time horizon of estimation (offline vs. online/real-time). Model-based methods are suited for conventional grids with detailed generator models. In contrast, the measurement-based techniques are better aligned with modern converter-interfaced systems through phasor measurement unit (PMU) data. The paper evaluates the strengths and limitations how different data types—ambient, ringdown, and probing—affect estimation strategies. This classification aims to support system operators and researchers in selecting appropriate IE strategies under diverse operating conditions and guides future development of inertia-aware control frameworks.**

Keywords*— *inertia estimation (IE) classification, model-based IE, measurement-based IE, on-line IE, off-line IE.

I. Introduction

The increasing penetration of renewable energy sources (RES) into power systems, driven by their numerous benefits, has led to a significant reduction in the power system inertia [1]. In conventional power grids dominated by synchronous generators (SGs), such as hydropower, nuclear, and thermal power plants, the rotating mass of SGs has typically provided a damping force that has contributed significantly to frequency stability. However, the growing prevalence of RES and the concomitant decline in SGs introduce multiple risks to power systems [2, 3], such as rapid frequency deviation, increased equipment stress, cascade failures and blackouts, and delayed response to disturbances.

These challenges underscore the need for innovative solutions to mitigate the impact of reduced inertia and ensure the reliable operation of power systems with a high penetration of RES. Inertia plays a crucial role in maintaining power system stability [4]. The literature presents a variety of methods for accurate and timely estimation of system inertia. Key indicators for inertia estimation include are nadir and rate of change of frequency (RoCoF). Nadir is defined as the minimum value of frequency following a disturbance, and RoCoF represents the rate at which the frequency changes [5].

Different power grids worldwide have established specific grid codes that define limits for permissible RoCoF and nadir values. For instance, while the United Kingdom allows a frequency deviation between 49.5 and 50.5 Hz, the normal operating limits are narrower, typically ranging from 49.8 to 50.2 Hz. Similarly, four Nordic countries (Denmark, Finland, Norway, and Sweden) have defined normal operating limits between 49.9 and 50.1 Hz [6]. Based on the frequency deviation limits specified in regional grid codes, three hierarchical levels of frequency response control strategies are typically employed to mitigate frequency deviations resulting from imbalances between generation and load. Table 1 presents a comparison of these control levels for the United Kingdom and the four Nordic countries. As indicated in Table 1, the grid code limits for frequency deviation are determined by the Transmission System Operator (TSO) and can vary between regions. The table provides response times and durations for three levels of frequency response control strategies in the UK and the Nordic countries of Denmark, Finland, Norway, and Sweden, along with the corresponding control objectives [7].

TABLE I. Different levels of frequency response control strategies for the United Kingdom and four Nordic countries [6, 7].

Control level	Response Time		Duration		Operation	Purpose
	Nordic	*UK*	*Nordic*	*UK*		
Primary control	0.7–1.3 s	2–10 s	5–30 s	20 s	Automatic	Intervene in response to frequency fluctuations to maintain the frequency value
Secondary control	10 s	10–30 s	30 s–2 min	30 min	Automatic	Employ control strategies to affect the return of system frequency to its nominal value and replenish the diminished power reserves of generators participating in primary frequency control.
Tertiary control	2–15 min	30 min	2–15 min	30 min	Upon request	Initiate control strategies to restore the depleted power reserves of generators engaged in secondary frequency control.

This paper introduces a novel two-dimensional classification framework for inertia estimation (IE) methods in power systems. The first dimension reflects the general methodological approach, distinguishing between model-based and measurement-based techniques. The second dimension is time-based, categorizing methods according to their estimation time horizon, such as offline (post-event) and online (real-time) approaches. Fig. 1 illustrates this framework, and Table 2 summarizes it.

This paper is organized as follows: Section II reviews the classifications of inertia estimation (IE) from two perspectives: general and time horizon. The conclusions and suggestions for future study are provided in Section III.

II. Inertia Estimation

This section discusses inertia estimation (IE) and its classification.

A. Basis of IE

To establish a foundation for inertia estimation, it is essential to first define the concept of inertia. In classical mechanics, Newton's first law describes inertia as the inherent tendency of an object to maintain its current state of motion unless acted upon by an external force [8]. Applying this principle to conventional power systems—comprising solely synchronous generators (SGs)—provides a basis for understanding system behavior prior to the integration of high levels of renewable energy sources (RES). In such systems, inertia arises from the kinetic energy stored in the rotating masses of SG rotors. This dynamic behavior can be mathematically represented using the swing equation, which is derived from Newton's second law of motion and formulated for a single generator as follows [9]:

$$2H_{SG}\frac{d\Delta\omega_g}{dt} = \Delta P_m - \Delta P_e - D\Delta\omega_g \tag{1}$$

where $\Delta\omega_g$ is the rotor speed deviation, and D is the damping factor. ΔP_m and ΔP_e are mechanical and electrical power, respectively. $H_{SG} = \frac{1}{2}J\,\omega_m^2/S_b$ is the inertia constant, which is the ratio between the rated power and the kinetic energy of the SG, where J is the moment of inertia, S_b is the rated power of SG, and ω_m is the rated rotor speed.

Synchronous generators (SGs), including hydroelectric, thermal, and nuclear power plants, have the magnitude of the inertia constant in the range of 1.75 to 10 s [10].

B. IE Strategy Classification

An accurate amount of inertia is required for secure and cost-effective operational decisions. The swing equation, which relies on the inertia in the system, is commonly used to determine the frequency response in power systems [11]. In general, the inertia estimation strategies fall into two classes: 1) model-based and 2) measurement-based inertia estimation, Fig. 1 [12].

Model-based IE: The model-based IE is embedded in the dynamic model of the SG. Model-based inertia estimation techniques, while widely used in SGs, are not directly applicable to RES-dominated grids or converter-interfaced generators (CIGs) that do not exhibit SG behavior, such as those not mimicking the swing equation. In general, model-based IE methods are divided into two categories that is shown in Fig. 1: 1) inertia estimation for a single SG and 2) inertia estimation for multiple SGs.

Measurement-based IE: In contemporary power systems, a measurement-based method is typically used to estimate the various system variables [13], because precise dynamic modelling of the system is not necessary. Power system operators are required to estimate the total inertia of their grids in near real time by using wide-area monitoring systems (WAMSs) [14]. Therefore, WAMSs are popular worldwide [15].

Rapid and accurate estimation of the inertial constants for large power systems is achieved through the utilization of a phasor measurement unit (PMU) [16, 17]. A PMU is a high-speed sensor with the capability to measure the voltage and current synchro-phasors at buses in the power grid with microsecond accuracy, and thus, they are faster than SCADA devices [18]. Three types of data can be extracted from the PMU depending on the disturbance size: 1) ambient data; 2) ringdown data; and 3) probing data. Table 2 shows the data categories for the PMU [19, 20]. When a system is operating in a normal state, ambient data, including information on small oscillations of load/generation, are collected [21]. After large disturbances, such as line tripping, sudden changes in loads, generator outages, and HVDC faults, ringdown data exhibit discernible oscillations [22, 26]. There are numerous inertia estimation techniques using the PMU measurement for power grids, microgrids, loads, and single generators. PMUs have measurement rates between 30 and 60 measurements per second for voltage, current, and power phasors in the system [23]. Although it is not generally a major concern, PMUs can monitor load feeders directly. The noise of a step change and the reaction delay determine whether the PMUs can allow inertia estimation or not [24]. Table 2 illustrates the measurement-based IE based on the extracted PMU data with their characteristics and the IE based on time instant. When a system is operating in a normal state, ambient data are collected, including small oscillations of load and generation [25]. In order to obtain probing data, usually low-level pseudo-random noise is purposefully injected into the power system [27].

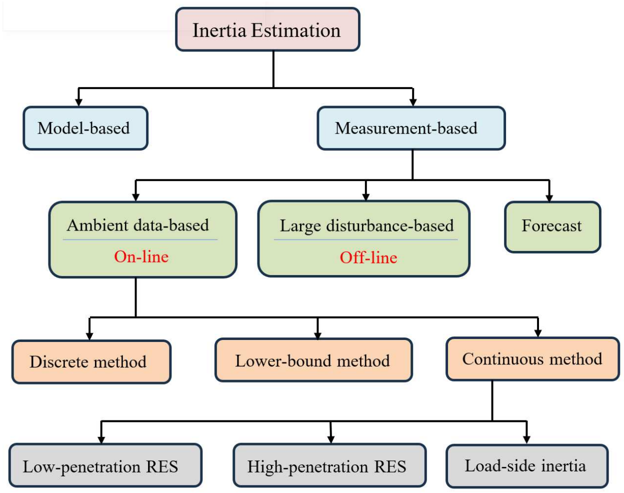

Fig. 1. Classification of IE in power systems, a two-dimensional classification of IE methods, considering both the general approach to IE and the specific time horizon perspectives.

TABLE II. MEASUREMENT-BASED IE RELYING ON THE EXTRACTED PMU DATA WITH THEIR CHARACTERISTICS AND THE IE BASED ON TIME INSTANT.

Time horizon	Off-line	On-line	
Data from PMU	Ringdown data	Ambient data	Probing data
Disturbance	Large disturbances	Normal operation (micro disturbances)	Low-level pseudo-random noise
Characteristics	• Line tripping • Sudden change in loads • Outage generators, HVDC faults	• Small oscillations of load/generation	• Filtered white Gaussian noise • Square wave pseudo-random binary sequence
Estimation window	Seconds	Seconds to Minutes	

C. Classification of IE Based on Time Horizon

Apart from the IE classification based on PMU data, there is another classification based on the time instant, divided into three main classes: 1) offline; 2) online; and 3) estimation of expected inertia [28]. Yet another approach for offline IE is postmortem analysis, which is used within an analytical setting to evaluate the inertia level of the system after large disturbances. Online IE is also known as a real-time method that seeks to quantify the inertia instantaneously by using readily accessible system variable measurements. Further, forecasting techniques calculate the estimated future inertia. Fig. 1 illustrates the IE classification.

Off-line, postmortem IE: When large frequency-disturbing events occur and the power imbalance associated with the rate of change of frequency is precisely understood, postmortem procedures calculate the inertia. In other words, in offline IE, the inertia after the event is estimated using the data that PMU collected immediately following the contingency or a large disturbance. Electrical power deviation is the main cause of power imbalance in the inertial response phase of power systems when they are exposed to a large disturbance. The reason for this is that the inertial response reacts more quickly than the generator governor. Consequently, the mechanical power keeps the inertial process in a constant state or very slightly modifies it [29], and damping is neglected, and thus, the inertia constant can be calculated by (2):

$$H_T = \frac{1}{2S_{rate}} \frac{-\Delta P_e}{\frac{d(\frac{\Delta f}{f_{rate}})}{dt}} \tag{2}$$

where S_r is the rated apparent power (base), and ΔP_e is the change in electrical power. In particular, there are three factors that determine how accurate postmortem methods are: 1) The accurate amount of loss should be determined. As a consequence, not every event will be appropriate for postmortem inertia calculation. 2) It is important to accurately identify exactly when that event began. 3) The precision of the RoCoF calculation has an impact on IE accuracy. In (2), ΔP_e is the electrical power deviation caused by some loads after disturbance, which are voltage- and frequency-dependent. On the other hand, the size of the disturbance can affect the deviation in the electrical power. Therefore, ΔP_e can be written as:

$$\Delta P_e = \Delta P_{Load} + \Delta P_{dis} \tag{3}$$

where the power variation of voltage- and frequency-independent loads is shown as ΔP_{Load} , and ΔP_{dis} determines the size of the disturbance [29]. It is considered that the value of the disturbance is known and constant by this method. This value could be known in some special cases, such as a generator outage or disconnection of a feeder. Nevertheless, not every event will provide an opportunity for an accurate measurement of the disruption [30]. Instead of using the rotor speed variation due to the unavailability of PMU measurement, the change in the generator frequency (RoCoF) can be used as a substitute. Calculating RoCoF by the differential of frequency measurements causes noise produced by coordinating the electrical power within the generators [31]. Because inertia and RoCoF are negatively correlated, contaminated data either exaggerate or underestimate the real value of inertia. Therefore, in order to achieve a more accurate calculation of ROCOF, various techniques have been devised to remove noise and abrupt transient-type changes in frequency measurements. To reduce the impact of oscillatory components, a 5th order polynomial in time is used to calculate the rate of frequency change [32]. Equation (4) represents the fifth order polynomial:

$$\frac{\Delta f}{f_{rate}} = A_5 t^5 + A_4 t^4 + A_3 t^3 + A_2 t^2 + A_1 t \tag{4}$$

where Δf defines the change in frequency, f_{rate} is the system's rated frequency, and t is the onset time of the event. A_1 to A_2 are calculated by the least square method. Thus, the (2) can be written as:

$$H_T = \frac{1}{2S_{rate}} \frac{-\Delta P_e}{A_1} \tag{5}$$

In addition to the above parameters, an accurate calculation of RoCoF requires knowledge of the exact time of the event onset; see, e.g. [31]. Furthermore, there are other means to eliminate the transient change and noise, such as 0.5 Hz and 5 Hz low-pass filters; however, these kinds of filters cause a time delay [33]. Another important factor in IE is the location of the installed PMU in order to reach the measurements; the closer the location of the PMU is to the event, the more accurate the RoCoF estimation is [34]. There is another algorithm for IE called the sliding window method (SWM), which uses a set of sliding data windows to concurrently estimate the inertia of the system and the time of the disturbance immediately following the disturbance [35]. This method filters the noise smoothly and uses the ringdown data for IE. It has been considered that to estimate off-line inertia, right after large disturbances, the TSO uses RoCoF and power imbalance magnitudes. Multiple challenges have been identified that influence the accuracy of the estimated magnitude of IE, e.g., variation in the power grid voltage that is due to disturbance-caused variation in the total power

TABLE III. KINETIC ENERGY CAPACITY OF THE POWER SYSTEM IN DIFFERENT REGIONS.

Region	Countries	Min./Max. kinetic energy capacity (GWs)
Nordic (Energinet, Fingrid, Statnett, Svenska Kraftnät)	Eastern Denmark, Finland, Norway, Sweden	125/240
UK (National Grid Electricity System Operator/National Grid ESO)	England, Wales, Scotland	130/not available
Reliability Council of Texas (ERCOT)	US	152/389
Australian Energy Market Operator (AEMO)	Queensland, Victoria, New South Wales, and South Australia	50/72
Eirgrid	Ireland	20/46

Consequently, off-line/postmortem inertia estimation employs moments after large disturbances in the power grid. The inertia estimated by this method is inaccurate due to the RoCoF/frequency nadir deviation in transient situations. Moreover, it is challenging to make a distinction between the primary response and the inertial response during the disturbance.

On-line, real-time IE: In contrast to the off-line/postmortem IE, which uses historical data right after large disturbances, there is another method called on-line/real-time IE that uses real-time measurements. Three categories are included in this approach from a chronological point of view [36]: 1) Continuous methods: based on the PMU's measurement of the frequency or power imbalance in the system; 2) Discrete methods: based on measurements of the PMU, during the time of disturbance, and close-to-real time IE; 3) Lower-bound methods: approximating the total share of SG units as a lower bound on the data from supervisory control and data acquisition (SCADA). Among these techniques, the continuous method is closest to real time. Fig. 1 shows the categorization of on-line/real-time IE. In the Nordic system, kinetic energy is estimated by (7); usually, a closed circuit breaker at the generation unit helps in this estimation [37].

$$E_{k,system} = \sum_{i=1}^{N} S_{ni} \,.\, H_i \quad [GWs] \tag{7}$$

where $E_{k,system}$ is the kinetic energy of the system. The inertia constant and the rated apparent power for generator i are represented by H_i and S_{ni}, respectively, and N is the number of connected generators. Table 3 presents the kinetic energy capacities of the power systems in different regions [37, 38].

Practical Implication: Several Transmission System Operators (TSOs) already apply inertia estimation methods consistent with this classification. For instance, the Nordic TSOs use offline post-disturbance analysis based on ringdown PMU data. National Grid ESO in the UK applies online, real-time estimation using continuous PMU signals. ERCOT in Texas combines offline analysis with real-time tracking, reflecting a hybrid approach. These examples highlight the practical relevance of the proposed framework.

III. CONCLUSION

The increasing integration of renewable energy sources (RES) has significantly reduced system inertia, introducing new challenges for power system stability and frequency control. In response, this paper proposed a revised classification framework for inertia estimation (IE) methods, structured along two key dimensions: the general methodological approach (model-based vs. measurement-based) and the estimation time horizon (offline vs. online/real-time).

Model-based techniques are well-suited for systems with a high share of synchronous generators, offering physically grounded formulations but requiring detailed dynamic models. In contrast, measurement-based methods leverage real-time data from phasor measurement units (PMUs), making them more applicable to converter-dominated systems, but they may be sensitive to data noise and measurement accuracy. The classification was further enriched by identifying three distinct PMU data types—ambient, ringdown, and probing—and mapping them to appropriate IE strategies.

As power systems evolve toward lower inertia and higher RES penetration, the development of robust, real-time, and adaptable inertia estimation frameworks will be essential for ensuring reliable and secure grid operation.

Despite the comprehensive nature of the proposed classification, its practical applicability remains to be validated under diverse operational scenarios and system conditions. Future research should therefore emphasize the implementation of these estimation strategies in real-world power systems and large-scale simulations. Moreover, the development of hybrid approaches—combining the strengths of model-based and measurement-based techniques—and the integration of data-driven methods, such as artificial intelligence and machine learning, may significantly enhance the accuracy, robustness, and adaptability of inertia estimation under high renewable penetration and low-inertia conditions.

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