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Advancements in Real-Time Estimation of Power System Inertia Considering Normal Load Variations – A Comparative Review

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Abstract: - The increasing trend in grid-integration of renewable energy sources (RES) into the power systems in conjunction with an overall decrease in the number of conventional generators results in a lower system inertia, which is crucial for power systems stability. Therefore, to implement the proper control measures to guarantee the stability of power systems in real-time, the estimation of power system inertia is necessary. Recent years have seen significant progress in real-time power system inertia estimation, particularly when taking normal load variations into account. This review aims at presenting the highlights of the developments made in recent years in this particular field. To effectively evaluate power system inertia in dynamic contexts considering normal load variations, researchers have concentrated on creating novel methodologies. The stability and reliability of power systems have to be greatly improved, by incorporating real-time data and novel advanced algorithms. The study critically evaluates and compares a range of inertia estimation methods in terms of accuracy, computational efficiency in real-time applications, adaptability to varying load conditions, robustness against disturbances, and overall reliability of the inertia estimation approaches.

Keywords: Renewable Energy Sources (RES), Inertia Estimation, Phasor Measurement Units (PMUs), Power System Stability, Ambient Conditions.

I. INTRODUCTION

As the third decade of the twenty-first century advances, the global energy environment is presently undergoing a major shift [1]. Global discussion over the future of our energy sources has intensified as a result of the urgent need to address climate change, energy security, and economic stability. The global energy transition is being guided by the increasing use of renewable energy sources (RES), which are no longer only seen as a substitute for conventional power sources but also as a key factor in radically altering our relationship with the environment and economy [2]. As renewable energy sources (RES) are increasingly included into the power systems, the power industry has undergone a substantial transition in recent years. The typical dynamics of power system operation have changed as a result of this move towards renewable energy and the corresponding noticeable reduction in the number of conventional generators. Consequently, there are now difficulties with grid stability and reliability due to the decreased overall inertia of the power grid [3], [4]. Renewable energy sources (RES) do not inherently contribute to system inertia in the same manner that conventional generators do because they are usually connected through power electronic converters [5]. The stability of electrical grids may be greatly compromised by the decline of inertia, particularly in the event of contingencies or abrupt fluctuations in the load conditions [6]. Due to the discontinuous nature of Converter Interfaced Generators (CIGs) and loads, Synchronous Generators (SGs) could have more frequent on/off switching, which would result in time-varying power system inertia [7]. Therefore, it is imperative for system operators to regularly monitor the inertia of power systems in order to implement control actions that successfully maintain grid security and reliability [8].

There are two primary approaches in the literature for estimating inertia of a power system. The first set of approaches involves utilizing frequency deviations and load variations following a malfunction or contingency, or by injecting a probing signal. The second set of approaches takes into account normal operating conditions [9], [10].

The main objective of this review article is to analyze the cutting-edge techniques for real-time, ambient condition-based power system inertia estimation and to identify research gaps that can be investigated in future work. When

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compared to disturbance-based approaches, these methods are more complex. The most significant benefit of these approaches is that they only require measurements obtained in ambient conditions, allowing for real-time estimation.

This review paper is structured as follows. Section II summarizes the novel methods for estimating the power system inertia in real-time considering ambient conditions. Section III presents discussion and commentary on the methods described in Section II, Section IV concludes the paper and Section V provides the directions towards the future work.

II. Inertia Estimation Methods

A. *Energy Variation-based Method and Q-Learning Algorithm*

Using Phasor Measurement Units (PMUs) measurements in ambient conditions, this approach continuously estimates inertia using electrical and kinetic energy variations. Additionally, a Q-Learning-based algorithm detects changes in mechanical power, which allows invalid inertia estimates to be discarded and further inertia estimates to be re-estimated [11]. All of the generator buses must have Phasor Measurement Units (PMUs) installed in order to employ the proposed approach to estimate power system inertia.

Figure 1 presents the proposed energy variation-based method (EVM) in terms of absolute error, which demonstrates the accuracy of the proposed inertia estimation approach in comparison with the system identification-based method (SIM).

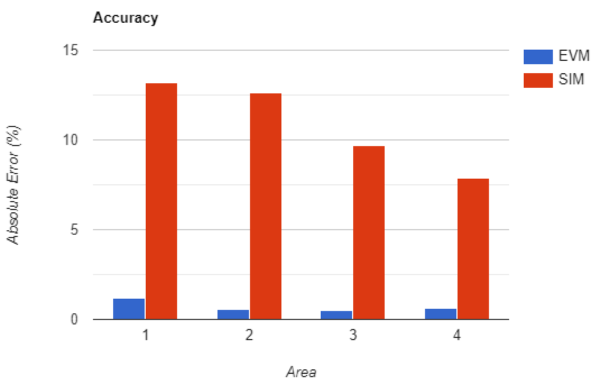

Fig. 1. Comparison of energy variation-based method (EVM) and system identification-based method (SIM) for area-level inertia estimation in terms of absolute error (%).

The accuracy and adaptability of the proposed approach are successfully demonstrated and validated using the IEEE 39-bus system. It has been demonstrated that compared to the method based on system identification, the suggested approach has much higher computing efficiency and better accuracy. Furthermore, the validity of the suggested approach has been verified at different noise levels.

The advantage of using Q-learning-based algorithm is that it does not require training and can be employed in real-time. The reward mechanism is adaptable and may be tailored to the requirements of the system. The technology is easily scalable to larger systems because of its high computational efficiency.

To determine whether the approach for estimating real-time inertia from renewable sources is applicable, more investigation is needed. Verification is also required for the performance of the algorithm with high penetration of renewable energy sources.

B. *Inertia Extraction from Unit Step Response and Inertia Monitoring using Sliding Window Method with Exponential Smoothing*

This approach incorporates a robust online power system inertia estimation method under ambient conditions and achieve a near precise inertia estimation with relative error below than 5% and can deliver the continuous monitoring of the inertial constant of a power system [12].

This study has made the following contributions:

- It provides a more accurate way of estimating the inertia constant of a power system under ambient conditions

- Under ambient conditions, the proposed approach achieves the estimation of the inertia constant at generator level, area level, and system level.
- Under ambient conditions, the proposed approach enables online monitoring of the inertia constant in time intervals of seconds, which can promptly offer vital data for the power system's stable operation.

The proposed method includes the following key steps:

a. Signal selection and preprocessing
b. System identification
c. Inertia constant extraction
d. Inertia constant monitoring

a. Signal selection and preprocessing

The dynamical model of a generator can be identified utilizing electrical power and rotor electrical frequency as the input and output respectively but the fact is, it is difficult to measure these quantities in the real power system. We can approximate electrical power and rotor electrical frequency by the active power output and bus frequency at the generator node bus respectively. In general, active power output and bus frequency can be measured by PMUs installed at the generator node bus and It can therefore, identify the dynamical model of the generator employing active power and bus frequency as input and output respectively.

Furthermore, it is attainable to identify the dynamical model of a particular area utilizing the cumulative active power and the accumulated frequency of the area as input and output respectively. The cumulative active power is obtained by summing up all the active power outputs in that particular area. However, for aggregating the frequency of the particular area, the study proposed a simplified accumulated frequency to represent the center of inertia (COI) frequency by the weighted average of the measured frequencies.

Signal preprocessing is an essential step before executing an identification algorithm to increase identification efficiency and precision because, under normal operating scenarios, the ambient data acquired by PMUs is often mixed with noise [13].

b. System identification

Subspace identification techniques, which can be applied in many ways, are efficient algorithms for identifying the state space model with ambient data [14]. This study employs the N4SID (Numerical algorithm for Subspace State Space System IDentification) approach. Singular value decomposition (SVD) is then used to determine the order of the model that has been identified. Model cross-validation should be performed to validate the identified model's reliability following the execution of the identification process. The validated output and the initial output are compared to complete the process.

c. Inertia constant extraction

The study offered a method for obtaining inertia constants at the generation node using the Swing equation. By using the swing equation and the proposed RoCoF calculation method, the inertia constant may be calculated from event measurements.

d. Inertia constant monitoring

The sliding window and exponential smoothing techniques provide real-time updates of the inertia constant. Under normal operating conditions, this method enables continuous tracking and monitoring of the inertia constant, offering insightful information for system stability and control. The performance of the sliding window method depends on the sliding window size and the estimated refresh rate. Despite the fact that the inertia constant obtained from the identified models can be updated online, a small number of low fitting ratio (FR) models might introduce imprecise estimates, causing the inertia constant to fluctuate significantly. The exponential smoothing method was applied to the low fitting ratio (FR) models estimates to smooth them.

The proposed approach was tested on IEEE 39-bus system. Table 1 presents the performance of the proposed approach for estimating inertia of each generator in terms of error (%).

Table 1. Performance of the proposed inertia estimation approach – Generator level

Generator	H_{ref} (s)	H_{avg} (s)	Error (%)
Gen 1	500.0	510.0	2.00

Generator	H_{ref} (s)	H_{avg} (s)	Error (%)
Gen 2	30.3	30.9	1.98
Gen 3	35.8	36.2	1.11
Gen 4	28.6	29.1	1.74
Gen 5	26.0	26.5	1.92
Gen 6	34.8	35.5	2.01
Gen 7	26.4	26.9	1.89
Gen 8	24.3	24.4	0.41
Gen 9	34.5	35.0	1.44
Gen 10	42.0	42.1	0.23

Table 2 presents the performance of the proposed approach for estimating inertia of each area and the whole system in terms of error (%).

Table 2. Performance of the proposed inertia estimation approach – Area and System level

Level	H_{ref} (s)	H_{avg} (s)	Error (%)
Area 1	500.0	510.0	2.00
Area 2	66.1	64.8	-1.96
Area 3	115.8	118.2	2.07
Area 4	100.8	104.4	3.57
System	782.7	757.9	-3.16

Using the IEEE 39-bus system, the proposed approach demonstrated high accuracy and low computational burden. The exact number of PMUs is not explicitly specified in the study. In one of the case studies involving the IEEE 39-bus system, PMUs were used to measure the bus frequency and active power output of all individual generators, indicating that each generator connection bus in the system was equipped with a PMU. By employing the proposed approach, the inertia constant could be updated on a time interval of seconds and real-time inertia constant tracking trajectories could be provided that indicate its robustness against disturbances and ability to handle dynamic changes in the system.

C. Inertia Estimation through Covariance Matrix

The article presented an online technique to match ambient measurements to the classical model of synchronous machines and estimate power system inertia based on these measurements by using the covariance matrix of these measurements [15].

The study exploits the colored noise caused by random variations in load power consumption and how these variations affect power flows, bus voltages, and line currents in various parts of a power system. The statistical characteristics of the colored noise of these electrical measurements are then analytically defined as functions of the system parameters and inertia of the system. Moreover, it minimizes a non-linear least-squares cost function in respect to the equivalent damping coefficients and inertia constants of the generators by utilizing the variation of the electrical measurements. The value of the damping coefficient or inertia constant that best fits the measurements and complies with the grid constraints is the solution. The key benefit of the suggested method is that it simply calls for ambient data and a basic understanding of the grid model.

For the first time, the proposed method shows how to estimate inertia using the covariance matrix of the power system, eliminating the need to determine the rotor speed or any other internal variable of synchronous machines and other frequency control devices. Two sets of linear ordinary differential equations (ODEs) can be solved to provide the mean and covariance matrix of the process.

The IEEE 39-bus system and the 1479-bus dynamic model of the All Island Irish Transmission System (AIITS) are used to evaluate the proposed methodology. To evaluate the active power output and bus frequency of each generator, PMUs are installed at the generator connection buses. Firstly, by taking into consideration conventional machines and their regulators, the IEEE 39-bus system allows to illustrate the various facets and challenges of the proposed technique. Next, the behavior of the proposed approach is assessed when grid-forming and grid-following converters are taken into account by the system. However, when used to a complicated real-world network, the all-island Irish transmission system (AIITS) demonstrates the reliability of the proposed approach.

Based on the numerical approach [16], the multi-dimensional Ornstein-Uhlenbeck (OU) process was numerically integrated in order to perform the simulations. Furthermore, [17], which can be found in the simulator PAN [18], [19], was chosen as the second-order trapezoidal implicit weak scheme for stochastic differential equations with colored noise.

a. Conventional Power System

The fgoalattain function and the MATLAB Global Optimization Toolbox were used to estimate the inertia constant. The optimization procedure search interval was lower bound to zero because inertia constants cannot be negative. The procedure performed 20 independent trials, each of which involved simulating the grid for 24 hours and solving an optimization problem every 15 minutes. This allowed for the collection of 1920 estimations for each synchronous generator. For Generator 5, the greatest percentage relative error in estimating the inertia was found to be 3.87%. For Generator 3, the minimal value of 0.44% is achieved. Before computing the moving variance subject to the considered currents, the quality of the findings can be enhanced by filtering them. This is achieved by removing the low-frequency contribution of the Ornstein-Uhlenbeck (OU) process using a steep bandpass filter that operates between 0.1 Hz and 1.5 Hz. The filtered currents are then employed to estimate the inertia constants of the IEEE 39-bus generators. As a result of this signal processing, the amplitude of the interval between the upper and lower adjacent values is significantly reduced, resulting in a more accurate approximation of the inertia constants. The percentage relative error in estimating the inertia ranges from 0.14% (Generator 2) to 1.78% (Generator 9). These results conclusively demonstrate that the proposed approach provides a more accurate estimation of power system inertia constants.

b. With grid-forming converters (GFMC)

The behavior of the proposed estimation method is demonstrated for an IEEE 39-bus system with grid-forming converters and a variable load profile. Such devices are meant to function similarly to synchronous machines, which means they should provide the system a virtual inertia. The percentage error for GFMC1, GFMC2, and GFMC3 in the high inertia case is 0.29%, 1.23%, and 0.60%, respectively. The percentage error in the low-inertia case is 0.02% and is about the same for all three grid-forming converters.

c. With grid-following converters (GFLC)

The proposed approach was used to discuss how frequency droop control in grid-following converters affects inertia estimate. The frequency droop control of the converter is comparable to that of synchronous machines, with the exception of significant damping and almost zero inertia, as it is analogous to a second-order model [20]. The results revealed a substantial correlation between the inertia and the estimation of damping/droop. The estimation of the inertia constant decreased as the droop coefficients of the frequency controller increased. This finding was expected since lower droop leads the controller to respond more slowly, and therefore its time scale tends to correspond with the inertial response. Based on the results of this scenario, it is concluded that the value of inertia alone is insufficient to determine the ability of a device to regulate frequency.

d. All-Island Irish Transmission System (AIITS)

Dome is a software tool used to obtain the AIITS time domain simulations [21]. The estimation of the inertia constants of eleven conventional synchronous power plants were chosen to be representative of non-homogeneous inertia constants and power ratings to demonstrate the applicability of the proposed method. This scenario has witnessed the percentage relative error in estimating the inertia ranges from 0.22% (Generator 7) to 5.42% (Generator 10).

The proposed approach, when the measurements are sufficiently filtered, can account for both virtual and conventional synchronous machines as well as the impact of frequency droop controllers and is accurate even in complex real-world systems. The proposed method also guarantees robustness when implemented in a complex practical systems.

There is no systematic procedure that specifies exactly where PMUs should be installed and linked to produce the measurements needed for the estimating process. This is an unresolved problem that may be investigated in future research.

D. RASSI Algorithm

The study presents a novel strategy for estimating the real-time inertia of an interconnected power system utilizing the identification of interarea electromechanical modes of oscillation acquired from ambient data [22]. The presented approach targets area-wise effective inertia estimation by deriving a link between inertia and interarea electromechanical modes of oscillation using an equivalent two-machine system derived from combining small signal stability analysis (SSSA) with power grid topology. The estimation scheme solely depends on the measurements from PMUs.

In this online inertia estimation scheme, the extraction of electromechanical oscillation modes based on Recursive Adaptive Subspace Identification (RASSI) algorithm [23] is carried out, which is computationally efficient and suitable for online tracking of the oscillation modes. The effective inertia is estimated using ambient data on voltage, current, and frequency acquired by the PMUs. The study does not specify the exact number of PMUs for the ambient measurements necessary for the inertia estimation.

Numerical simulation is carried out on IEEE 16-generator system for evaluating the accuracy of the proposed scheme. A modal analysis based on the small signal stability analysis (SSSA) is performed with the system with ambient conditions and the interarea oscillation modes are extracted by applying RASSI algorithm. It is evident that the number of electromechanical modes that RASSI algorithm was able to extract from the ambient data is consistent with the number found in the model analysis. Furthermore, the extracted modes are concentrated within a narrow range around the theoretical value, as indicated by the mean and standard deviation. Based on accurately extracted electromechanical modes of oscillation, effective inertia of area-1, area-2 and area-345 is estimated. The sum of the inertia values are considered for demonstrating the accuracy of the estimation results. The statistical evaluation has been performed and the findings are shown in Table 3.

A few values in the effective inertia estimate findings deviate greatly from the theoretical value in continuous time, which is limited by the unpredictability of the ambient data. This portion of the value, however, does not reflect the outcomes of the estimation.

The proposed approach is then applied to real measurements of a power grid (NM and DB) in North China to check its vali-

dation and adaptability. The effective inertia of the NM and DB power grid are estimated by the ambient measurements obtained by PMUs. Table 4 shows the statistical results of the estimated values for 5 minutes.

Table 3. Inertia estimation statistical results in different operating conditions (Opc)

		Estimated Value		
Area	**Actual Value (s)**	**Basic Opc (s)**	**Opc 2 (s)**	**Opc 3 (s)**
		Mean Std	**Mean Std**	**Mean Std**
1	30.67	32.31 2.68	33.15 3.07	28.31 2.12
2	65.48	63.92 3.24	62.59 2.96	66.09 3.32
345	108.95	93.38 8.17	92.48 14.15	95.74 14.15

Table 4. Inertia estimation statistical results for NM and DB power grids

		Estimated Value (s)
Power Grid	**Theoretical Value (s)**	**Mean Std**
NM	16.14	18.43 2.55
DB	307.85	375.17 27.6

According to the statistical results, the mean estimated inertia of NM power grid is close to the theoretical inertia, while it deviates larger in the DB power grid. Thus, from the estimation results of NM power grid, it is verified that the proposed approach is efficient and feasible for realistic systems and measurements.

The proposed approach shows better accuracy for inertia estimation in areas 1 and 2 (simulation) and with the NM power grid (real measurements) however, the proposed study does not account for the computational efficiency of the proposed approach and is not adaptable to load variations and disturbances.

E. An Improved Algorithm for Online Inertia Estimation in Power Grids with Renewable Energy Sources (RES)

This Paper [24] critically analyzed and modified the N4SID algorithm employed in [12], to effectively estimate the power system inertia constant continuously under ambient conditions from the real-time measurements obtained from PMUs.

The proposed approach involves estimating a linear model that connects changes in frequency on a bus to variations in active power and then extracting the inertia constant from the unit-step response of the identified model. With the IEEE 39-bus system, the estimation algorithm used in [12] showcased satisfactory results but it has accounted for poor performance in case of IEEE 14-bus system and this reason lead the authors of this paper to analyze and modify the algorithm [12] to get improved performance.

Initially, the simulation is carried out with the modified algorithm on IEEE 14-bus system without PV panel. PMUs are installed at six buses (1, 2, 3, 6, 8 and 11) in the IEEE-14 bus system, which is crucial for measuring the variations in frequency and active power at these generator buses. The N4SID algorithm [12] automatically identifies a system with an order between 1 and 10 by calculating the order that produces the least estimation error. As it happens, a more accurate system identification does not always reflect in a more accurate inertia estimation. In order to demonstrate this, a simulation performed with window size 10 and an order variation from 1 to 8. Table 5 presents the analysis results for each generator and the system as a whole. It shows that using higher-order systems, as performed in [12], results in a systematic underestimation of inertia because the initial slope of the step response is repeatedly steeper than that of the first-order system.

Table 5. Fitting ratio and estimation error on generators and whole system for order 1 and 4

	Fitting Ratio	Estimation Error
Order	**1 4**	**1 4**
Whole system	9.9e-4 9.3e-6	-0.195 -9.792
Gen 1	5.4e-4 1.4e-6	-0.327 -10.554
Gen 2	4.1e-3 8.8e-6	0.185 -19.055
Gen 3	4.9e-3 1.9e-6	0.563 -18.707
Gen 6	2.5e-2 3.1e-6	4.774 -38.545
Gen 8	1.0e-2 7.2e-6	-2.207 -29.889

Choosing an appropriate window length is also an influencing factor for monitoring the inertia constant continuously [25]. A systematic investigation on the whole system (first order) is carried out on how window length affects data fitting quality and the inertia estimation in terms of fitting ratio and root mean square (RMSE). It is observed that for a window length of 5s, the change in inertia is noticed with a very small delay of about 5s, but the estimated inertia showed considerable oscillations, that suggested a greater RMSE value. It is reversed for window length 50s and for window length 10s, there was a reasonable trade-off between delay and RMSE.

In order to allow for a flexible refresh rate, it is more effective to create a new system estimates only in the event that the data from the prior estimate does not fit the current window. The proposed approach defined a refresh condition on the basis of the fitting ratio and the percentage that separates the number of estimations from the total number of time frames and investigated the effect of changing refresh condition on the performance of the inertia estimation and on the number of new system estimations. It is found that the number of new system estimations decreases with increasing refresh conditions, but the percentage of inaccuracy on the mean value of the estimated inertia constant increases as well.

The improved algorithm is then implemented on IEEE 14-bus system with the inclusion of PV panels (RES). The system is simulated under ambient conditions for 1000s. Table 6 shows the estimated inertia values of the whole system (with the RES) and all generators. For the grid as a whole and generators 1-3, the percentage estimation error is less than 2%. For generators 6 and 8, which have substantially lower rated powers than the others, higher values of inertia are attained.

It is noticed that a shorter update time could be possible with the maximum computation time of 0.15s for system identification and inertia estimate, which is roughly half of the computation time taken by the actual algorithm [12].

Table 6. Performance of inertia estimation for IEEE 14-bus system including renewable energy sources (RES)

	Actual Inertia	Estimated Inertia	Error %
System (with RES)	10.00	9.95	-0.50
Gen 1	5.14	5.15	0.19
Gen 2	6.54	6.59	0.76
Gen 3	6.54	6.65	1.68
Gen 6	5.06	5.56	8.82
Gen 8	5.06	5.33	5.33

By taking into account both synchronous generators and RES, the improved algorithm enables more precise estimation of the total system inertia. The requirement for parameter calibration particular to the power system under observation is addressed by this improved algorithm. This modification guarantees that the algorithm operates at its best under various grid designs and operational circumstances.
The improved algorithm seeks to incorporate the estimation of the Centre of Inertia frequency (f_{COI}), which may provide a comprehensive assessment of grid dynamics and stability. The development of criteria for self-tuning particular parameters is one area of future research for the improved algorithm, which may enhance the adaptability and reduces computational burden during estimation.

F. Online Tracking of Inertia Constants based on Sliding Window Method using Ambient Measurements

The proposed approach is based on the sliding window strategy to estimate the inertia constants of conventional synchronous generators, virtual synchronous generators and virtual power plants by utilizing ambient measurements of the power system [26].
There are several drawbacks and limitations with the existing techniques for estimating inertia constants that rely on ambient data. In reality, for these techniques to work well, longer observation times (hundreds of seconds or more) are typically needed [12], [27]. Computational efficiency is highly affected by the increase in the window length, impeding the real-time update of inertia estimates. Furthermore, the order of the generated transfer function, has a significant impact on the accuracy of these existing methods. Either iterative techniques or transfer functions with various orders must be generated to address this problem. Also the identification process may result in unstable transfer functions because of issues with data quality [28]. Hence, the identified models in the previously mentioned cases are not feasible for inertia estimation.
In this proposed method, ambient measurements of frequency and active power are recorded at the terminals of generation devices. Further, the Auto-Regressive Moving Average eXogenous (ARMAX) method is used to develop low-order transfer function models. In contrast with conventional methods, the proposed approach presents low computational complexity by identifying inertia constants using small monitoring windows. Because of this property, the suggested approach can be used in real-time applications. It is important to note that user-defined parameters such as order of the developed transfer function models, essentially have no impact on the computational efficiency of the proposed method. The proposed method guarantees robustness by developing an automated procedure for identifying unreal inertia estimates due to poor data quality. As a result, exogenous variables like the amount of disturbance in measured responses do not affect the accuracy of the proposed approach.
The proposed method is validated on IEEE 9-bus system. The PMUs are located at the connection buses of Generator 1, Generator 2, and Generator 3, and at the point of common coupling (PCC) of the Virtual Power Plant with the Transmission System at Bus MV1. Monte Carlo (MC) Simulations are performed to measure the effect of various factors such as noise/disturbance level, window length, data refresh rate, and approximation order on the performance of the proposed approach. The proposed method approaches the real inertia constant quickly, with prediction errors of less than 2.5% for any device under consideration. The performance of the proposed approach is proven unaffected by the approximation order with mean value of the prediction error less than 2% in all cases ($n = 2$ to 6) and the prediction error for measuring the impact of window length in all combinations ($n = 2$ to 6) of model orders is also less than 2%. Furthermore, the refresh rate is slightly unaffected to the accuracy of the proposed approach. The proposed approach assesses the effect of noise on its performance by applying additive white Gaussian noise (AWGN) to the simulated environmental responses. To replicate two levels of signal-to-noise (SNR) ratios, the AWGN variance is changed. The median prediction error value is significantly less than 5% for both SNR levels, confirming the efficiency of the method in noisy environments. For all cases, an execution time less than 0.5s is recorded that implies that the proposed strategy is suitable for applications involving near-real-time monitoring.
The proposed approach is also tested on IEEE 39-bus system. For generator level inertia constant and overall system inertia constant, the prediction error is evident to less than 5%, confirming the accuracy of the proposed approach.

G. Power System Inertia Estimation using Synchrophasor Data with an Ambient Modal Framework

This novel approach developed an analytical framework [29] for estimating and monitoring real-time power system inertia which is based on the frequency and damping ratio modes obtained from normal operating conditions.
The proposed approach consists of simulating ambient responses, extracting electromechanical oscillation modes, formulating inertia estimation based on these modes, and validating the approach through numerical simulations and physical testing.

The Power System Toolbox (PST) [30] is used to carry numerical simulations on a single-generator infinite bus system. The ambient responses of the power system are simulated by applying a random load with a Gaussian distribution and a defined amplitude. Stochastic Subspace System Identification (SSI) method is used to extract electromechanical oscillation modes from synchronized ambient data. The extracted modes contain frequency and damping ratio, which are critical for inertia estimates. The inertia constant is obtained using the oscillation modes identified from synchronized ambient data. The connection between inertia and electromechanical modes is established using modal analysis theory, which allows for the estimate of inertia using extracted modes and steady-state variables.

Table 7 presents a statistical comparison of the results for the extraction of the electromechanical oscillation frequency and damping ratio, which demonstrates that the extracted modes' mean value with subspace system identification (SSI) is comparable to the results of small-signal stability analysis (SSSA) with a small standard deviation.

Table 7. Statistical results of extracted modes with small signal stability analysis (SSSA) and subspace system identification (SSI)

Method	Frequency (Hz)	Damping ratio (%)
SSSA	0.747	5.303
SSI	Mean=0.758 Std=0.008	Mean=5.594 Std=1.169

Two methods of calculation are taken into consideration. In order to get 500 inertia estimation results, the first strategy computes the inertia for each simulation using the extracted modes and steady-state variables. In order to get a single inertia estimation result, the second strategy computes the inertia using the means of the extracted modes and steady-state variables in 500 simulations. In the first strategy, the estimation results randomly fluctuate (in a small range) around the actual value. Table 8 presents the estimation results based on different model orders.

Table 9 presents the estimation results based on a physical test and demonstrates the accuracy of the proposed method. The mean estimated value is closer to the actual value in both the strategies and also the standard deviation is considerably small for the second strategy.

Table 8. Inertia estimation statistical results based on different model orders

Model order	Actual value Mean	First strategy Mean	Second strategy Mean Std
2^{nd}	2.85	2.855	2.859 0.0388
6^{th}	2.85	2.787	2.794 0.0382
6^{th} with exciter	2.85	2.916	2.921 0.0367

Table 9. Inertia estimation statistical results based on physical test

Actual value Mean	First strategy Mean	Second strategy Mean Std
1.585	1.768	1.717 0.0478

Numerical simulations and actual measurements showed that the proposed approach has excellent computation efficiency and robust performance under ambient excitation conditions. The results reveal that the proposed strategy yields close estimates of real inertia values, showing its accuracy as well as effectiveness for online applications.

H. Data-Driven Inertia Estimation based on Frequency Gradient

This proposed data-driven approach uses the gradient frequency of an estimated system model to estimate time-dependent inertia. The suggested method employs ambient measurement data from PMUs, which is then used to estimate a dynamical model that mimics the system [31]. One of the innovative aspects of the suggested strategy is the use of a decomposition technique to decrease redundant higher order model estimates from the system identification approach, hence reducing computational effort and facilitating RoCoF analysis. The other novelty of the proposed strategy is that, it is simple to estimate and extract inertia from the estimated system model by using the coordinated frequency gradient mapping on the RoCoF of the frequency response of the system.

A system identification method driven by a large dataset results in a complex model with a higher-order transfer function. This higher-order model requires a high computational power and is challenging to analyze [32]. Also, the addition of noise in frequency response in these higher-order models can result in inaccurate inertia estimates [33]. Hence, it is crucial to minimize the order of the model without sacrificing critical data. It is vital to estimate the reduced model in such a way that allows it to capture essential system dynamics. Therefore, the obtained model is reduced to a low but optimal order that captures the desired dynamics of the system. Singular Value Decomposition (SVD) technique is employed in this proposed approach for obtaining optimal order reduction. The oblique projection vector is subjected to the SVD.

It is reasonable to determine the total system inertia in multi-input multi-output (MIMO) system models by considering the center of inertia (COI) frequency of the system [34]. The COI frequency is obtained by calculating the average area frequencies weighted by the inertia of each area [35]. The proposed approach applied a unit-step signal to the reduced-order transfer function model and used the modified window method to determine the gradient of the frequency response. From there, the inertia constant of the system is computed employing the initial gradient of the estimated model of the unit step response.

Using a modified IEEE 39-bus system, simulations are performed in DIgSILENT™ Power Factory tool, to verify the proposed strategy. It can be inferred that all PMUs installed at the generator connection buses are utilized to achieve a comprehensive set of measurements for inertia estimation. Table 10 presents the statistical performance of the proposed approach for estimating effective inertia (system-level) in terms of error (%).

Table 10. Statistical performance of the proposed approach for estimating effective inertia (system-level)

Simulation	Actual inertia constant (s)	Estimated inertia constant (s)	Error (%)
		Mean Std	
1	3.87	4.21 0.51	8.79
2	4.65	4.32 0.54	7.10
3	5.56	5.33 0.59	4.14
4	7.69	7.19 0.50	6.50
5	8.12	8.66 0.53	6.65
6	9.21	9.79 0.47	6.30
7	10.02	10.59 0.31	5.69

Table 11 presents the statistical performance of the proposed approach for estimating effective inertia with RES penetration in terms of error (%).

Table 11. Statistical performance of the proposed approach for estimating effective inertia with RES penetration

RES penetration (%)	Actual inertia constant (s)	Estimated inertia constant (s)	Error (%)
		Mean Std	
0	7.69	7.25 0.36	5.72
10	6.98	6.55 0.39	6.16
15	6.05	6.44 0.33	6.45
20	5.16	5.52 0.23	6.98

The method is fairly accurate in estimating the values of inertia in systems under normal operational settings, as indicated by the low variations between the actual and estimated values of inertia for the investigated system for both scenarios, which range from 4.14% to 8.79%.

The proposed method is also simulated using the measurements of a real system – New Zealand grid. The estimation results from the real measurements strongly advised to employ a COI bus for signal measurements in order to ensure optimal performance of the proposed approach. To obtain high inertia estimation accuracy in power systems, this strategy necessitates an appropriate selection of a COI bus.

I. Real-Time Inertia Estimation using Local Rational Model Approach

The article proposed an online data-driven technique for estimating the virtual inertia of converter-based devices and the inertia constant of synchronous generators, enabling time-dependent inertia monitoring in ambient operating scenarios of a power system [36]. The method relies on ambient data from Phasor Measurement Units (PMUs) and does not require any particular parametric assumptions, which makes the estimation of inertia robust. Because of its adaptability to varying loads and operating conditions, the approach is a versatile tool for measuring inertia at the generator, area, and system levels.

The proposed strategy is predicated on the ongoing observation of the frequency response functions of converter-based and synchronous generator devices, which are detected using ambient PMU measurements. To find frequency response functions, a unique non-parametric technique known as the Local Rational Model (LRM) [37] is used. This method does not require model order selection. To estimate time-dependent inertia from ambient data, the LRM technique has a minimal processing cost and requires a short data frame [38].

To evaluate the efficiency of the proposed approach, simulation on the IEEE 39-bus system are performed in DIgSILENT^{TM} Power Factory tool. PMUs are installed at each bus with synchronous generators (SGs) and converter-based resources (CBRs) in the IEEE 39-bus system. Table 12 presents the performance of the proposed approach in estimating inertia of all the generators and converter-based devices (CBDs) in different sizes of data frame in terms of percentage maximum relative error (RE). The fact that the relative error of the estimated inertia is less than 4% across all data frames indicates the proposed strategy is accurate. Table 13 presents the performance of the proposed approach in comparison with other methods in terms of percentage relative error, data frame length and running time.

Table 12. Performance of the proposed approach in estimating inertia in different sizes of data frame

Generator	Actual Inertia (s)	Estimated inertia (s)			Max RE (%)
		T=600s	T=100s	T=20s	
Gen 1	5.000	5.0211	4.9826	5.0026	2.11
Gen 2	4.329	4.3295	4.2961	4.4075	1.81
Gen 3	4.475	4.4768	4.4489	4.5536	1.76
Gen 4	3.575	3.6095	3.5656	3.6136	1.08
Gen 5	4.333	4.3798	4.3163	4.4908	3.64
Gen 6	4.350	4.4064	4.3526	4.3841	1.30
Gen 7	3.771	3.8211	3.7922	3.7830	1.33
Gen 8	3.471	3.4817	3.4655	3.5048	0.97
Gen 9	3.450	3.4525	3.4382	3.5804	3.78
Gen 10	4.200	4.2111	4.1874	4.2323	0.77
CBD1	3.000	3.0228	3.0514	3.0915	3.05
CBD2	7.000	7.0164	7.0431	7.0621	2.07

From the results presented in Table 13. It is evident that the proposed strategy , which incorporates a short frame of ambient data—a critical component of real-time inertia estimation—is accurate and computationally efficient for estimating inertia.

Table 13. Performance of the proposed approach in comparison with other methods in terms of relative error, data frame length and running time

Method	RE (%)	T(s)	Running time (s)
[39]	16.0	240	90
[40]	5.0	20	4
LRM	1.9	20	0.65

Table 14 presents the performance of the proposed approach in estimating effective inertia of different areas and the entire system. The accuracy of the proposed approach in calculating the effective inertia of areas and the total inertia of the system is demonstrated by the relative error of estimated inertia, which is less than 3% in all data frames.

The proposed data-driven method which is based on the LRM framework is an effective approach for estimating inertia in modern power systems, since it is accurate, robust against disturbances, adaptable to load variations and has a low computational cost.

Table 14. Performance of the proposed approach in estimating effective inertia of different areas and the entire system.

	Actual Inertia (s)	Estimated inertia (s) T=600s T=100s T=20s	Max RE (%)
Area 1	3.6187	3.6439 3.6404 3.6795	1.68
Area 2	4.0972	4.1258 4.1235 4.1604	1.54
Area 3	5.0816	5.1326 5.1304 5.2057	2.44
System	4.6267	4.6937 4.6979 4.7541	2.75

III. Discussions And Commentary

Table 15 compares the various novel approaches for estimating power system inertia in real-time in terms addressing accuracy, computational efficiency, robustness against disturbances and adaptability to load variations.

Table 15. Comparison of real-time power system inertia estimation approaches in terms of demonstrating accuracy, computational efficiency, robustness against disturbances and adaptability to load variations

Method	Accuracy	Computational efficiency	Robustness against disturbances	Adaptability to load variations
A	✓	✓	✓	✓
B	✓	✓	✓	✓
C	✓	✓	✓	✓
D	✓	×	×	×
E	✓	✓	✓	✓
F	✓	✓	✓	✓
G	✓	✓	×	✓
H	✓	✓	×	×
I	✓	✓	✓	✓

Methods A, B, C, E, F, and I excel in all four categories, demonstrating high accuracy, computational efficiency, robustness against disturbances, and adaptability to load variations. This indicates that these methods are highly reliable and versatile for real-time applications. Method G, while accurate and computationally efficient, lacks robustness against disturbances but maintains adaptability to load variations. Similarly, Method H is accurate and efficient but falls short in both robustness and adaptability, suggesting limitations in dynamic and varying conditions.

On the other hand, Method D shows a significant drop in performance, failing to meet the required standards in computational efficiency, robustness, and adaptability, despite being accurate. This suggests that while Method D can provide precise measurements, it struggles with real-time implementation and adaptability to load changing conditions. Overall, the comparison highlights the strengths of methods A, B, C, E, F, and I in providing comprehensive solutions for real-time inertia estimation, with G and H offering partial solutions, and D needing significant improvements for practical use.

Table 16 enlists the concentration of various novel approaches in estimating inertia in real-time. This categorization highlights the diverse applicability and versatility of different methods in real-time power system inertia estimation, reflecting their potential for use in various scenarios within power system operations.

Table 16. Concentration of various Inertia estimation approaches

Method	Inertia estimation concentration (level)
A	Area
B	Generator, Area, System
C	Generator, GFMs, GFLs
D	Area, System
E	Generator, System
F	Generator, System
G	System
H	System
I	Generator, Area, System, CBDs

IV. Conclusion

The growing inclusion of renewable energy sources (RES) and the corresponding decline in conventional generators have created a critical need for accurate and efficient inertia monitoring. This article addresses this need by providing a thorough review of various novel methods in estimating real-time inertia of a power system considering ambient conditions. The review highlights how crucial accurate inertia estimation is to preserving grid stability and reliability. It assesses several approaches by contrasting their accuracy, computational efficiency, robustness against disturbances, and adaptability in response to changes in load. Benefits and drawbacks of each method are examined, offering an understanding of its potential for real-time monitoring as well as its usefulness in real-world scenarios. The review also points out research gaps for future research and provides recommendations for advancements and further investigation into how well these techniques work, especially in systems with significant RES penetration. Overall, the study emphasizes how advanced inertia estimation methods are required to guarantee the stable operation of modern power systems amidst the ongoing energy transition.

V. Future Directions

The paper highlights a significant problem regarding the optimal location of Phasor Measurement Units (PMUs) to guarantee accurate estimation of power system inertia. To optimize inertia estimation accuracy and efficiency, future research should provide methodical processes and algorithms to identify the optimal placement of PMUs in a power grid. It is imperative to improve the adaptability of inertia estimating techniques to accommodate different dynamic scenarios and complex power systems. Studies should look into how these techniques can be adjusted or improved to deal with various grid topologies, operational situations, and unforeseen disturbances. The accuracy of inertia estimates may be further improved by the application of sophisticated algorithms, based on machine learning and artificial intelligence. It is necessary to create self-tuning algorithms that can tune parameters in response to real-time data and altering grid conditions in order to increase the robustness and adaptability of inertia estimation techniques. This would guarantee optimal performance in a variety of settings and reduce the requirement for manual tuning. Inertia estimates at several hierarchical levels, such as generator, area, and system levels, should be further investigated in research. A thorough evaluation will aid in the implementation of focused control measures and offer a more thorough understanding of the distribution of inertia throughout the power grid.

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