RESEARCH ARTICLE

Applications of Curve Fitting Techniques in Inertia Estimation of Power System

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Abstract

The integration of renewable energy sources (RES) into modern power systems is transforming the traditional reliance on synchronous generators, leading to a greener energy portfolio while posing significant challenges to system stability due to reduced inertia. Diminished system inertia results in elevated rates of change of frequency (RoCoF) and larger frequency deviations, potentially culminating in blackouts. Accurate inertia estimation is paramount for implementing virtual inertia control and enhancing frequency support services. This study investigates curve-fitting techniques, with a focus on polynomial fitting, for inertia estimation. Simulations are conducted on a modified IEEE 9-bus system incorporating dynamic models. Transient events involve 10% and 20% load increases at t = 10 s. Results demonstrate that fifth-order polynomials yield the minimum errors (e.g., 9.61% for the 10% load case), with robustness to data loss maintaining errors below 2% for up to 20–30% data reduction.

Keywords: curve fitting, frequency stability, IEEE test systems, polynomial fitting, power system inertia, renewable energy sources.

1 Introduction

The modern power system, traditionally reliant on synchronous generators, is increasingly incorporating renewable energy sources (RES), such as wind and solar power [1]. While RES contribute to a greener energy portfolio, they pose challenges to system inertia, which is essential for maintaining stability [2]. Diminished system inertia results in higher rates of change of frequency (RoCoF) and larger frequency deviations from the nominal value, potentially leading to system blackouts [3]. Accurate inertia estimation is crucial for implementing virtual inertia control and enhancing frequency support services [4]. Low-inertia systems experience amplified RoCoF and larger frequency nadirs, increasing the risk of cascading failures [6].

Inertia estimation methods are classified into model-based, measurement-based, and data-driven approaches. Model-based techniques often struggle with real-time accuracy in dynamic RES environments [7]. Measurement-based methods are sensitive to noise [8]. Data-driven methods require extensive training data [9]. Curve-fitting techniques, particularly polynomial fitting, offer simplicity in

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approximating frequency trajectories and estimating RoCoF [10]. However, their sensitivity to polynomial order and data length remains a challenge [11]; gaps persist in the systematic evaluation of polynomial order and data length on estimation accuracy. This paper addresses the effects of these parameters under load disturbances by simulating scenarios on the modified IEEE 9-bus benchmark, evaluating errors, and proposing enhancements for frequency stability.

The remainder of the paper is organized as follows: Section 2 details the mathematical modeling and methodology; Section 3 presents simulation results and discussions; and Section 4 concludes with findings and future scope.

2 Mathematical Modeling and Methodology

This section outlines the mathematical foundations and procedural framework for estimating power system inertia using curve-fitting techniques. It draws on established power system dynamics models, particularly the swing equation for frequency response analysis, and applies polynomial curve fitting to post-disturbance data. Simulations are conducted on the modified IEEE 9-bus benchmark test system to evaluate the method's performance under various conditions. The impact of polynomial order and data length on estimation accuracy is emphasized, aligning with recent advancements in inertia estimation for renewable-integrated grids.

The frequency response of a power system to disturbances is governed by the swing equation, which describes the dynamic behavior of synchronous generators in response to power imbalances. For an equivalent synchronous generator representing the system, the swing equation is expressed as:

$$\frac{2H_{\text{sys}}S}{f_0}\frac{df}{dt} = P_m - P_e - D\Delta f \tag{1}$$

where P_m and P_e are the total mechanical and electrical active power in MW, respectively; f_0 is the nominal frequency (typically 50 Hz or 60 Hz); f is the measured system frequency in Hz; df/dt is the RoCoF in Hz/s; H_{sys} is the system inertia constant in seconds; S is the system base power in MVA; and D is the load damping coefficient (per unit). This formulation captures the inertial response during the initial transient phase following a disturbance, such as a load change or generator trip [1, 3].

Damping effects (D) can often be neglected during the brief period immediately after a power mismatch [17], simplifying the equation for multi-machine systems to:

$$\frac{2H_{\text{sys}}S}{f_0}\frac{df}{dt} = P_m - P_e \tag{2}$$

For small perturbations around an operating point [5], this can be linearized as:

$$\frac{2H_{\text{sys}}S}{f_0}\frac{d\Delta f}{dt} = \Delta P_m - \Delta P_e = \Delta P \tag{3}$$

where ΔP represents the total power imbalance (MW) during the transient. The system inertia H_{sys} for a network with N synchronous generators is aggregated as:

$$H_{\text{sys}} = \frac{\sum_{i=1}^{N} H_i S_i}{\sum_{i=1}^{N} S_i} \tag{4}$$

with H_i and S_i being the inertia constant (s) and rated apparent power (MVA) of the i-th generator.

Assuming governor response lags ($\Delta P_m \approx 0$), (3) simplifies to:

$$H_{\text{sys}} = \frac{1}{2S}\cdot\frac{-f_0\Delta P_e}{\frac{df_{\text{COI}}}{dt}} = \frac{1}{2S}\cdot\frac{\Delta P}{\frac{d(\Delta f/f_0)}{dt}} \tag{5}$$

Polynomial curve fitting is applied to $\frac{\Delta f}{f_0}$ [16]:

$$\frac{\Delta f}{f_0} = A_n t^n + A_{n-1}t^{n-1} + \cdots + A_1 t \tag{6}$$

with the derivative yielding $\frac{d(\Delta f/f_0)}{dt} = A_1$, leading to:

$$H_{\text{estimated}} = \frac{\Delta P}{2SA_1} \tag{7}$$

The polynomial order n critically affects accuracy. Standard IEEE test systems are modified to incorporate dynamic models [7]. The IEEE 9-bus system is selected [18], with a base frequency of 50 Hz and base power of 100 MVA. Step load increases (10% and 20%) at t=10 s are simulated using PowerWorld Simulator interfaced with MATLAB. The modified IEEE 9-bus test system is shown in Figure 1. Error in inertia estimated (H_{error}) is calculated as [5]:

$$H_{\text{error}}(\%) = \left|\frac{H_{\text{true}} - H_{\text{estimated}}}{H_{\text{true}}}\right| \times 100 \tag{8}$$

where H_{true} is the known aggregated inertia. Simulation results and discussions are presented in subsequent sections. The overall methodology is summarized in Figure 2, which integrates simulation data processing, disturbance identification, fitting, and error calculation.

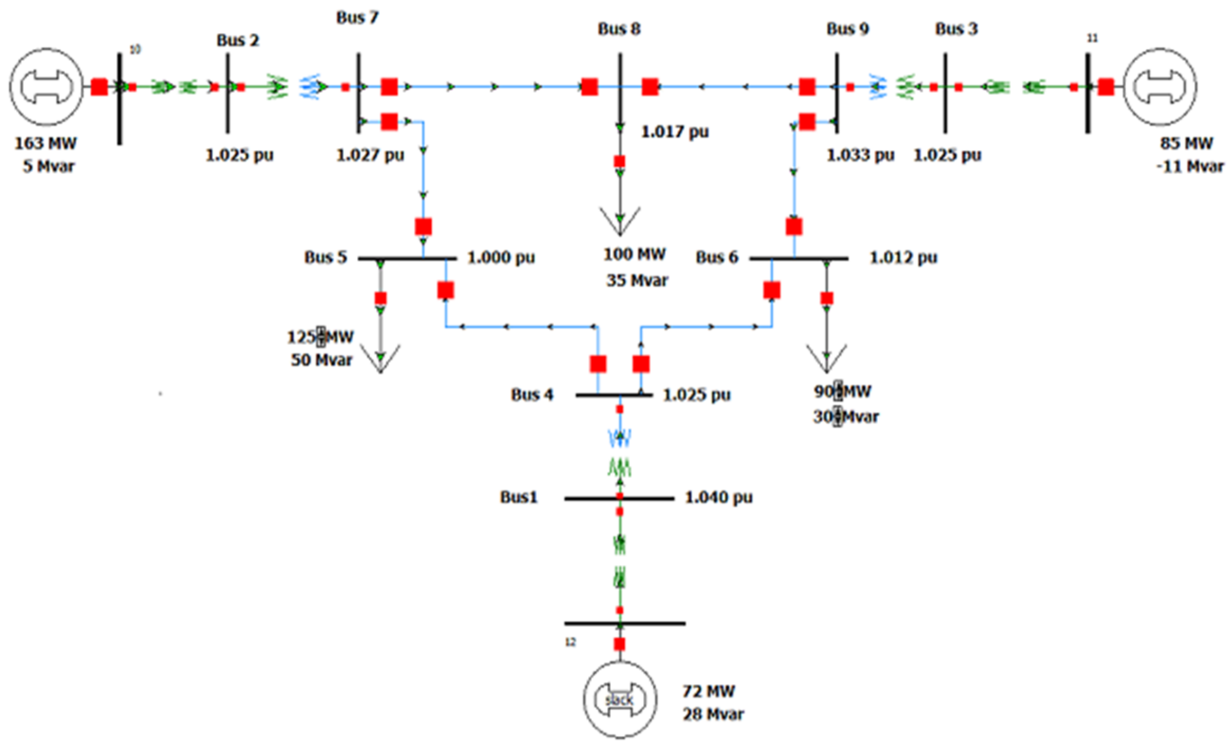

Figure 1. Modified IEEE 9-Bus test system.

Table 1. Error (%) in the IEEE 9-Bus system.

Order of Polynomial	4th	5th	6th	7th	8th	9th
Estimation Error (10% Load Increase)	94.68	9.61	38.27	41.60	48.00	64.03
Estimation Error (20% Load Increase)	90.29	10.52	37.62	39.38	44.53	61.94

3 Results and Discussion

This section presents the outcomes of simulations conducted on the modified IEEE 9-bus test system, focusing on polynomial curve fitting for power system inertia estimation. Results derive from time-domain transient simulations using PowerWorld Simulator, interfaced with MATLAB for data processing and curve fitting via the Curve Fitting Toolbox. Step load increases of 10% and 20% from the base load on the largest load bus at t=10 s serve as disturbances, with data collected over 100 s (approximately 250,000 points per case). Frequency and power data are filtered using a 50 ms moving average to mitigate noise, as commonly applied in RoCoF estimation studies to enhance accuracy [8]. Estimation errors are evaluated under varying polynomial orders (fourth to ninth) and data lengths, highlighting trends in accuracy and robustness. Discussions integrate comparisons with established literature on inertia and RoCoF estimation, emphasizing implications for low-inertia grids with high renewable penetration.

Simulations demonstrate the dynamic response of the test system to load disturbances, capturing frequency deviations at generator buses and power output variations from synchronous machines. These outcomes align with expected behaviors in power systems, where reduced inertia exacerbates frequency excursions and RoCoF, as noted in comprehensive reviews of inertia estimation methods [2, 8]. The system stabilizes around t=45 s post-disturbance, consistent with governor and exciter response times in IEEE models [7].

Frequency trajectories post-disturbance illustrate the inertial response, with initial drops reflecting power imbalances and subsequent recovery via primary control. Polynomial fitting applied to these curves derives RoCoF, showing improved accuracy with higher orders, as supported by studies on

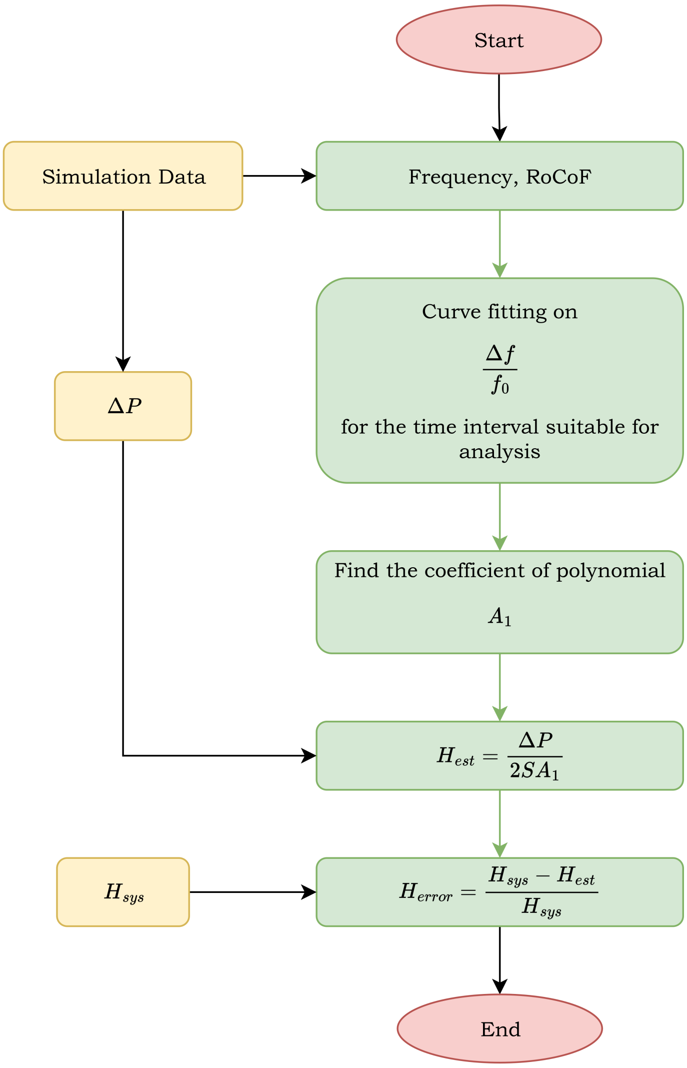

Figure 2. Flow chart for inertia estimation by curve fitting.

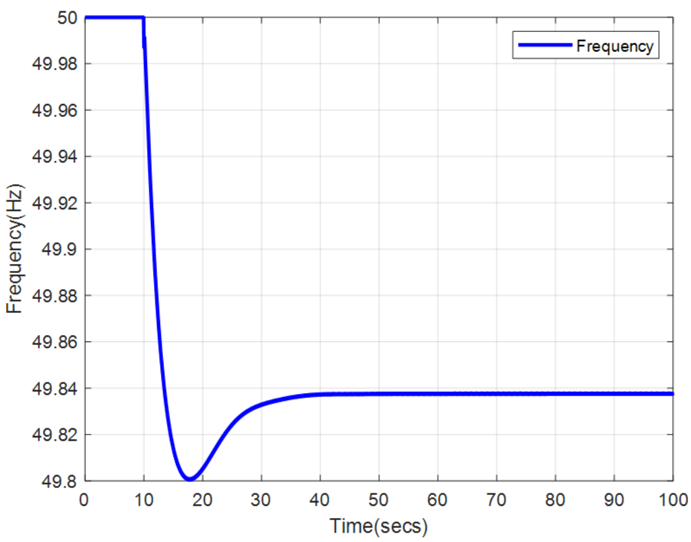

Figure 3. Frequency variation at bus 1 under 10% load increase.

variable-order polynomials for frequency response approximation [2, 5]. Figure 3 shows the frequency variation at Bus 1 under a 10% load increase, indicating higher RoCoF for larger disturbances and underscoring inertia's role in limiting deviations [8].

Generator power outputs ramp up to compensate for load increases, with initial surges reflecting inertial contributions before governor action. This behavior corroborates findings in inertia estimation reviews, where power imbalance data enhances RoCoF accuracy [3, 10]. Figure 4 shows the power variation for generator 1 under a 10% load increase.

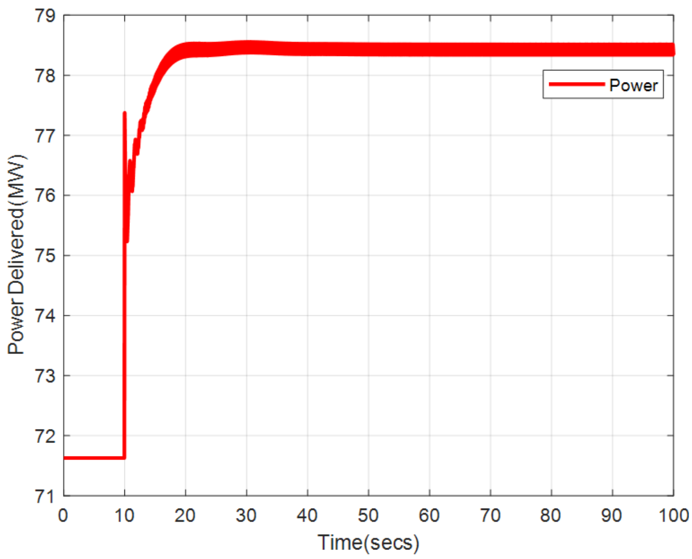

Figure 4. Power variation for generator 1 under 10% load increase.

The impact of polynomial order on inertia estimation error is assessed using the swing equation-derived (7), where errors exceed 100% at low orders due to underfitting [15]. Polynomial orders from fourth to ninth are tested, with errors calculated via (8). Optimal performance occurs at the fifth order, aligning with literature on avoiding overfitting in RoCoF fitting [12, 14]. The fifth order yields minimum errors, with higher orders indicating overfitting and lower orders underfitting, as shown in Table 1 (true inertia: IEEE 9-bus $H_{\text{sys}} = 3.3617$ s).

Data loss resilience is evaluated by simulating measurement gaps common in PMU data [11]. Data windows are reduced from full (10–45 s) by 5 s increments. Errors increase near-linearly, but fifth- to seventh-order polynomials remain robust up to 20 s, echoing findings in uncertainty analyses for varying inertia [1, 11]. Errors for selected orders (fifth, sixth, seventh) and loads are shown in Table 2.

Fifth-order polynomials optimize inertia estimation (errors $< 10\%$), balancing underfitting (low orders)

Table 2. Error percentages due to data loss in the IEEE 9-Bus system.

Order	Load	10–45 s	15–45 s	20–45 s
5th	10%	9.61	40.61	59.15
5th	20%	10.52	37.91	47.57
6th	10%	38.27	38.27	31.59
6th	20%	37.62	39.62	31.66
7th	10%	41.60	33.97	77.99
7th	20%	39.38	35.75	78.43

and overfitting (high orders), as corroborated by evaluations of polynomial methods in low-inertia contexts [4, 5]. Higher orders increase computational complexity without accuracy gains, making them unsuitable for real-time applications [7]. Data loss impacts are manageable up to 20–30% reduction ($< 50\%$ error for fifth-order), supporting resilience in noisy PMU environments [11]. These findings advance curve-fitting techniques, with potential extensions to machine learning-enhanced adaptive orders [7, 13].

4 Conclusion

Polynomial curve fitting of fourth- to sixth-order provides high accuracy and reliability for inertia estimation, outperforming lower-order approximations. Key findings from rigorous simulations on the standardized IEEE 9-bus test system include reduced estimation errors with higher polynomial orders and resilience to data loss up to 20–30%. These results lay a foundation for enhancing grid stability and frequency regulation in sustainable power systems. A limitation is the assumption of negligible damping. Future work could extend to alternative fitting functions, Bayesian uncertainty quantification, integration with machine learning for adaptive order selection, and validation under high renewable energy sources penetration scenarios.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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