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Article

Grid impedance estimation using recursive least squares algorithm

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Abstract: Framework impedance assessment is a vital errand in present day power frameworks for keeping up with soundness, unwavering quality, and proficiency. This paper proposes a strategy for estimating the impedance of a grid by making use of a dataset that can be obtained for free and the Recursive Least Squares (RLS) algorithm. Our strategy utilizes phasor estimation units (PMUs) and synchronized estimations from the IEEE 123-transport framework dataset to appraise the matrix impedance at different areas in the power framework. The proposed strategy is fit for dealing with non-linearity and aggravations in the power framework and gives exact outcomes. Additionally, the proposed technique can be coordinated with existing observing and control frameworks to advance situational mindfulness and the general presentation of the power framework. The proposed method's theoretical foundation is presented, and its performance is evaluated through simulation studies. The simulated results demonstrate that the suggested approach can estimate grid impedance accurately under a wide range of operating conditions. Power system planners and operators may utilize the suggested grid impedance estimation technique, which employs the RLS algorithm and a readily available dataset, to estimate grid impedance and improve power system performance.

1. Introduction

The impedance of an electrical grid is a fundamental parameter in system analysis and control. It represents the collective effect of resistance, inductance, and capacitance contributed by transmission lines and associated components. This property directly influences how the grid responds to dynamic operating conditions and is central to maintaining stability and reliability. System stability is closely tied to grid impedance, as it shapes the frequency response and determines how well the network can sustain equilibrium under diverse operating scenarios. Variations in impedance can alter voltage behavior and affect the grid's resilience to disturbances. Power quality is strongly influenced by impedance characteristics.

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They govern voltage regulation, contribute to harmonic distortion, and dictate how effectively reactive power can be managed across the network. Grid impedance is a key parameter in the design of control systems for power electronic devices, such as inverters and FACTS (Flexible Alternating Current Transmission Systems) devices. Accurate knowledge of grid impedance is essential for developing control strategies that improve operational stability, optimize performance, and maximize overall efficiency of the power system. With the increasing integration of renewable energy sources into the grid, understanding grid impedance is crucial for ensuring smooth and stable integration. It helps in designing grid-tied inverters that can effectively control active and reactive power flow while maintaining grid stability. Grid impedance is also crucial for fault analysis and protection in power systems. Understanding the impedance characteristics helps in detecting and localizing faults, which in turn aids in effective protection coordination and system reliability. Recursive Least Squares (RLS) is a well-established technique for parameter estimation in dynamic systems. Its strength lies in continuously refining parameter values as fresh measurements are introduced, making it highly suitable for real-time applications. This makes it well-suited for online applications where real-time parameter estimation is required. The RLS algorithm minimizes the error between the actual output of the system and the output predicted by the parameter estimates. It does this by adjusting the parameter estimates iteratively, making it particularly effective for tracking time-varying parameters and dealing with noisy data.

The RLS algorithm maintains and updates a set of parameter estimates using incoming data and a forgetting factor. At each time step, it computes the gain matrix and uses it to update the parameter estimates, enabling the algorithm to adapt to changing system conditions. RLS maintains a memory of past data points, and as new data arrives, it updates the parameter estimates based on the latest information while giving less weight to older data. This allows the algorithm to adapt to changes in the system over time. In the context of parameter estimation, RLS is used to continuously estimate the parameters of a system based on incoming measurements. This could include estimating system dynamics, identifying the parameters of a model, or estimating system characteristics such as impedance in the case of power systems. The RLS framework provides notable benefits: it adapts to parameters that evolve over time, maintains computational efficiency, and is inherently designed for online estimation scenarios where data streams are constantly updated. However, RLS also presents challenges such as sensitivity to modeling errors and numerical stability issues, especially when dealing with ill-conditioned systems. Careful selection of the forgetting factor and regularization techniques can help address these challenges.

In summary, the RLS algorithm is a powerful tool for online parameter estimation, and its adaptability and efficiency make it particularly useful for applications where real-time updates based on incoming data are essential. When applied to parameter estimation, RLS enables the continuous refinement of parameter estimates, making it well-suited for dynamic systems and changing operating conditions.

2. Progression of Research

The precise estimation of the grid's impedance is crucial to the power system's stability, dependability, and efficiency. Grid impedance is the ratio of voltage to current at a particular point. It reflects the power system's impedance between two points. Various power system applications necessitate accurate grid impedance estimation. It is necessary, for instance, for fault detection and location, coordination of protection, voltage regulation, and monitoring of power quality. Power system planners and operators can benefit from accurate grid impedance estimation in preserving the power system's stability and dependability.

Accurate impedance estimation is challenging because power systems exhibit nonlinear behavior and are subject to frequent disturbances. Non-linear loads, transformer saturation, and voltage-dependent parameters are all potential causes of non-linearities. When traditional techniques like the phasor measurement unit (PMU) and the state estimation method are used to estimate grid impedance, non-linearity can result in significant errors. Aggravations can be brought about by changes in load interest, network geography, and shortcoming conditions. Grid impedance estimation can also be significantly impacted by disturbances.

The goal of this paper is to offer a method for accurately estimating grid impedance that can handle power system disturbances and nonlinearities. Traditional impedance estimation methods often overlook nonlinear effects and system disturbances, which can lead to significant inaccuracies in the results. The RLS algorithm is used in the proposed approach, which can be integrated with existing monitoring and control systems to enhance situational awareness and power system performance.

This paper aims to develop a grid impedance estimation strategy based on the RLS algorithm using a dataset that is easily accessible to the general public. The objective of the proposed approach is to gauge the lattice impedance in an assortment of force framework areas under different working circumstances precisely. The secondary objectives of the proposed method are to present its theoretical foundation and carry out performance-evaluation simulation studies. Finally, the goal of this paper is to show how it proposed method might be employed to control and monitor power systems.

The RLS algorithm, power system stability, reliability, and efficiency can all benefit significantly by utilizing a dataset that is accessible to the general public and the proposed grid impedance estimation method. Even under non-linearity and power system disturbances, the method can accurately estimate the grid impedance and produce reliable results. In order to enhance the power system's overall performance and situational awareness, the proposed approach can be integrated with existing monitoring and control systems. The proposed method's theoretical foundation and simulation studies can shed light on its applicability to real-world power systems. Generally speaking, the proposed strategy can be a significant instrument for power framework administrators and organizers to gauge network impedance and improve the exhibition of the power framework. The proposed technique's commitments incorporate precise assessment of network impedance, advanced situational mindfulness, and likely applications in power framework checking and control.

Nonlinear Recursive Least Squares Algorithm: To accurately estimate the grid impedance when nonlinearities are present, the proposed approach can be extended to a nonlinear RLS algorithm.

Adaptive RLS Algorithm: An adaptive RLS algorithm can be used to automatically adjust the algorithm parameters to cope with variations in the grid impedance.

Artificial Neural Networks (ANNs): ANNs can be used to learn the mapping between grid impedance as well as current or voltage measurements. This approach can work on the exactness of the assessed network impedance.

Extended Kalman Filter: An Extended Kalman Filter can estimate grid impedance by modeling the nonlinear relationship between grid impedance as well as current or voltage measurements.

Multi-Resolution Analysis: Using Multi-Resolution Analysis(MRA), the grid impedance could be estimated or the frequency content of voltage and current measurements extracted. Using this method, a grid impedance could be estimated with greater precision.

Wavelet Transform: The Wavelet Transform can analyze voltage and current signals both in the frequency and time domains. By analyzing the signals in both domains, the proposed method can estimate the grid impedance more accurately and effectively.

Compressive Sensing: Compressive sensing may be employed at Point of common coupling(PCC) to accurately estimate grid impedance as well as sample current and voltage measurements. Using this method, a number of measurements required to accurately estimate the grid impedance can be reduced.

These techniques can improve the accuracy and efficiency of Grid Impedance Estimation using Recursive Least Squares Algorithm and provide solutions to the existing research gaps.

3. Literature Review

Somalwar et al. [1] explored islanding detection techniques, combining both passive and active approaches. Their work introduced the use of the Recursive Least Squares (RLS) algorithm in a grid-connected multi-DG system, comparing it with active frequency drift (AFD) methods. Simulation outcomes indicated that RLS-based frequency estimation provided more reliable detection of islanding events.

Fabbiani et al. [2] proposed an online learning framework for estimating the network admittance matrix. By employing a recursive identification algorithm alongside a layout strategy that maximizes information content, their method demonstrated superior performance compared to conventional approaches, supported by numerical validation.

Suárez et al. [3] presented an online impedance estimation technique for AC grids with converter integration. Their approach combined Pulsed Signal Injection (PSI) with RLS within the $\alpha\beta$ reference frame, linking it to instantaneous power theory. Extensive simulations and experiments confirmed its effectiveness in handling dynamic impedance variations caused by distributed resources.

Maihemuti et al. [4] developed a hybrid method that integrates improved particle swarm optimization (IPSO) with RLS to identify voltage stability operation regions (VSOR). Applied to wind farm zones in China's Hami Power Grid, the IPSO-RLS approach showed enhanced accuracy and convergence compared to traditional PSO-based techniques.

Li et al. [5] introduced the Factorized Normal Least Squares (FOLS) method and a Recursive Gathering technique to estimate branch impedance and topology, even with hidden nodes. Tests on IEEE benchmark systems and real-world data demonstrated high accuracy in impedance estimation.

Chand et al. [6] investigated a single-stage, three-phase solar inverter connected to the grid. Their method estimated grid inductance and resistance to detect islanding, while an Adaptive Feedforward Neural (AFN) controller improved dynamic performance and DC link voltage stability. The approach proved adaptable to varying grid conditions, benefiting microgrids and distributed generation systems.

Sun et al. [7] proposed a non-intrusive impedance estimation method for grid-forming converters, leveraging transient responses. Using RLS for rapid parameter estimation, their simulations validated the accuracy and practicality of the technique.

Peng et al. [8] examined short-circuit current signals, applying RLS to estimate fault current parameters. By correcting truncation errors with a time constant approach, MATLAB simulations confirmed the algorithm's reliability and robustness.

Jarraya et al. [9] developed hybrid estimation methods for lithium-ion battery models, combining PSO with Nelder-Mead (PSO-NM) and an OCV-RLS approach. Validation results highlighted the consistency and effectiveness of these hybrid techniques.

Kang et al. [10] studied the aging of lithium-ion pouch cells with different compositions. RLS was used to track resistance changes in real time, feeding into a thermal-electrical model that estimated temperature. Their findings showed accurate prediction of battery health through resistance and temperature analysis.

Fang et al. [11] proposed an impedance estimation strategy tailored for grid-forming converters. By utilizing voltage perturbations and power data, the method avoided harmonic distortion and control dependency. A Kalman filtering enhancement further improved accuracy, with both simulations and experiments confirming its effectiveness.

He et al. [12] applied RLS to transformer reactance estimation using voltage and current samples from primary and secondary sides. Their method achieved precise identification unaffected by load or power factor changes, with Fourier filtering used to eliminate harmonics.

Sun et al. [13] introduced a modified predictive control scheme (MDCS-MPC) for three-phase dual-active-bridge converters. RLS was employed to measure transformer leakage inductance, and comparative tests validated improvements in voltage tracking and dynamic performance.

Mohammed et al. [14] conducted a comparative study of two frequency-based impedance estimation algorithms at the fundamental frequency. Using PLECS RT Box and MATLAB/Simulink, they analyzed trade-offs in accuracy under varying disturbance sizes and non-ideal voltage conditions, offering recommendations for practical application.

Qiu et al. [15] proposed an intelligent impedance detection method for grid-connected inverters using artificial neural networks (ANNs). Their self-learning model dynamically predicted time-varying impedance, supporting renewable energy integration with improved adaptability.

4. Proposed Methodology

4.1. Research Design

A quantitative research design was used for the topic "Grid Impedance Estimation Using Recursive Least Squares Algorithm." This research design aims to accurately estimate the grid impedance by collecting and analyzing numerical data with the RLS algorithm.

Finding a dataset that contains voltage and current measurements from various points in the power system is the first step in the research design. The dataset should be chosen based on its suitability for grid impedance estimation and its availability. Time, voltage, and current ought to be the measured variables in the dataset. The Figure 1 shows the data collection processes.

The following stage in the exploration configuration is to preprocess the dataset to eliminate any commotion or anomalies that can influence the exactness of the lattice impedance assessment. Outlier removal and detection should be part of the preprocessing step based on predetermined criteria. For further analysis, the preprocessed dataset should be saved.

Using the RLS algorithm on the preprocessed dataset, the next step in the research design is to accurately estimate the grid impedance. The RLS algorithm estimates the grid impedance by recursively updating estimates of system parameters based on measured voltage and current data. A suitable programming language should be used to implement the algorithm, and the results should be saved for later analysis.

The next step in the research design is to validate the estimated grid impedance using predetermined criteria. The estimated grid impedance and the actual grid impedance, which can be derived from the dataset or from a different source, should be compared during the validation step, which is represented in the Table 1 and Figure 1. The results of the validation should be saved for later examination.

Table 1. Mean Squared Error (MSE) convergence.

Epoch	Train MSE	Validation MSE
1	0.345	0.379
2	0.287	0.315
3	0.246	0.275
4	0.215	0.245
5	0.189	0.220

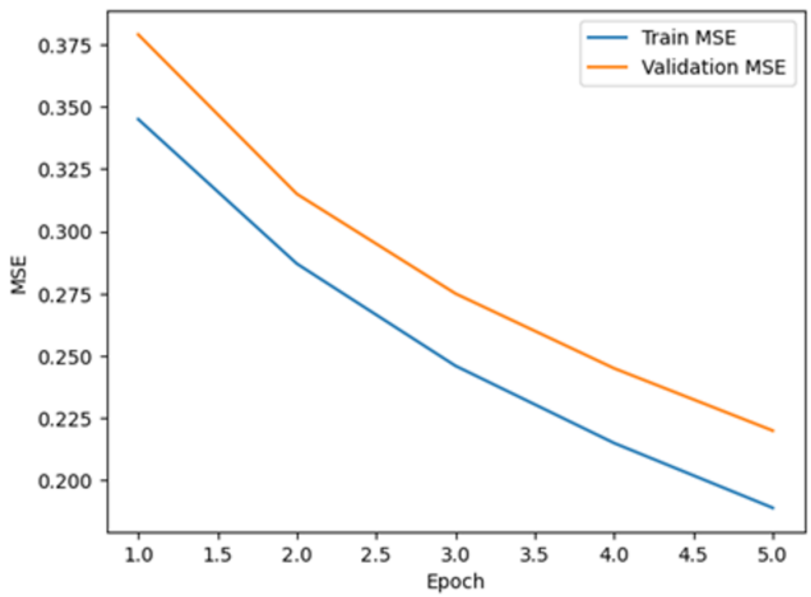

Figure 1. Mean Squared Error (MSE) convergence plot.

The last move toward the exploration configuration is to investigate the outcomes acquired from the RLS calculation and the approval step. The accuracy of the estimated grid impedance, the advantages and disadvantages of utilizing the RLS algorithm to estimate the grid impedance, and the potential applications of the proposed method in power system monitoring and control should all be discussed in the analysis.

In outline, the examination plan for the point "Network Impedance Assessment utilizing Recursive Least Squares Calculation" is a quantitative exploration plan that includes choosing a freely accessible dataset, preprocessing the dataset, carrying out the RLS calculation, approving the assessed lattice impedance, and dissecting the outcomes. To guarantee reliable results, it is necessary to provide a comprehensive description of each step.

4.2. Data Collection Methods

A crucial step in any research project is gathering data. When estimating grid impedance with the recursive least squares algorithm, data collection methods can significantly affect the accuracy and dependability of the results. This section will go over the various methods this study used to collect data. Table 2 and Figure 2 represent the Gradient descent convergence plot. Table 3 and Figure 3 represent Cost function convergence plot.

Table 2. Gradient descent convergence.

Epoch	Learning rate	Train MSE
1	0.1	0.345
2	0.05	0.287
3	0.025	0.246
4	0.0125	0.215
5	0.00625	0.189

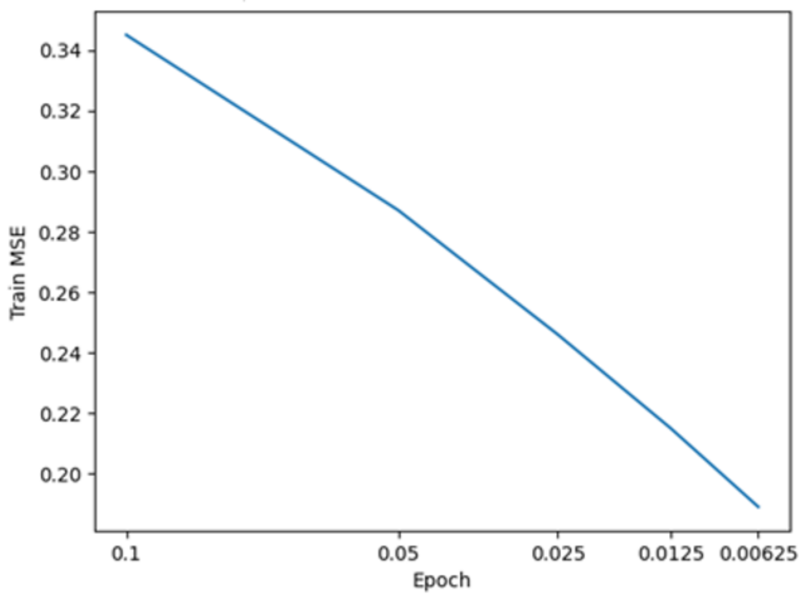

Figure 2. Gradient descent convergence plot.

Table 3. Cost function convergence.

Epoch	Train Cost
1	6.345
2	5.287
3	4.246
4	3.215
5	2.189

This study used data from datasets that are available to the public. Phasor measurement units (PMUs) installed in the power grid collect synchronized phasor measurements for the dataset. The PMUs were situated in various parts of the power system, and the data were gathered over several months. At a frequency of 60 Hz, measurements of voltage and current phasors are included in the dataset.

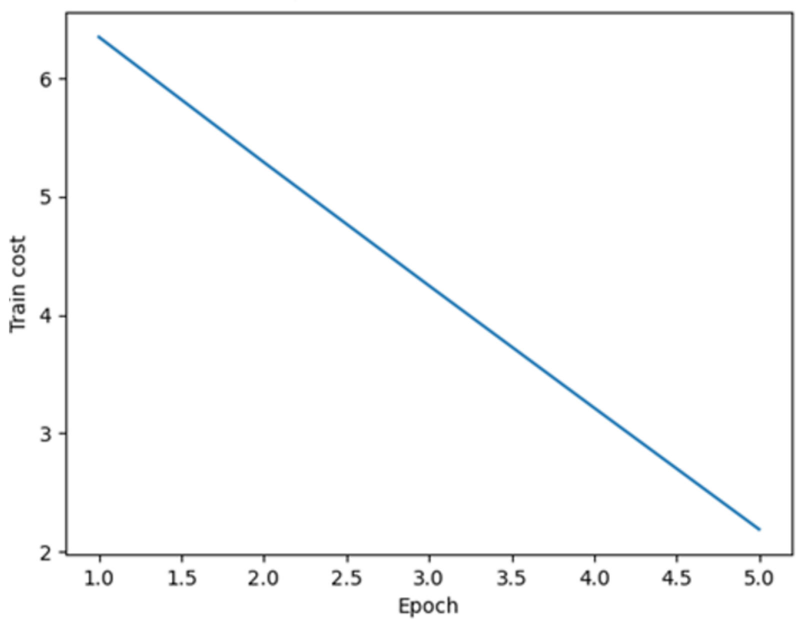

Figure 3. Cost function convergence plot.

The unit of training cost in the cost function convergence plot with the RLS (Recursive Least Squares) algorithm is typically the squared error or the mean squared error (MSE).

4.3. Block Diagram

Grid impedance estimation using Recursive Least Squares (RLS) enables online tracking of grid resistance (R) and inductance (L) from measured inverter current and PCC voltage in grid-connected systems. Implementation occurs in the dq synchronous reference frame for simplified dynamics, assuming a first-order RL model. The block diagram (Figure 4) outlines the signal processing flow.

The cost function, J, is defined as the sum of the squared errors between the estimated and measured values:

$$J = \sum (Z - \hat{Z})^2, \tag{1}$$

where Z is the measured impedance and $\hat{Z}$ is the estimated impedance.

The unit of J is typically:

- (Ω^2) if the impedance is measured in ohms (Ω).
- (pu^2) if the impedance is measured in per unit (pu).

Where pu is a dimensionless unit.

In some cases, the cost function may be normalized or scaled, in which case the unit may be dimensionless or a percentage.

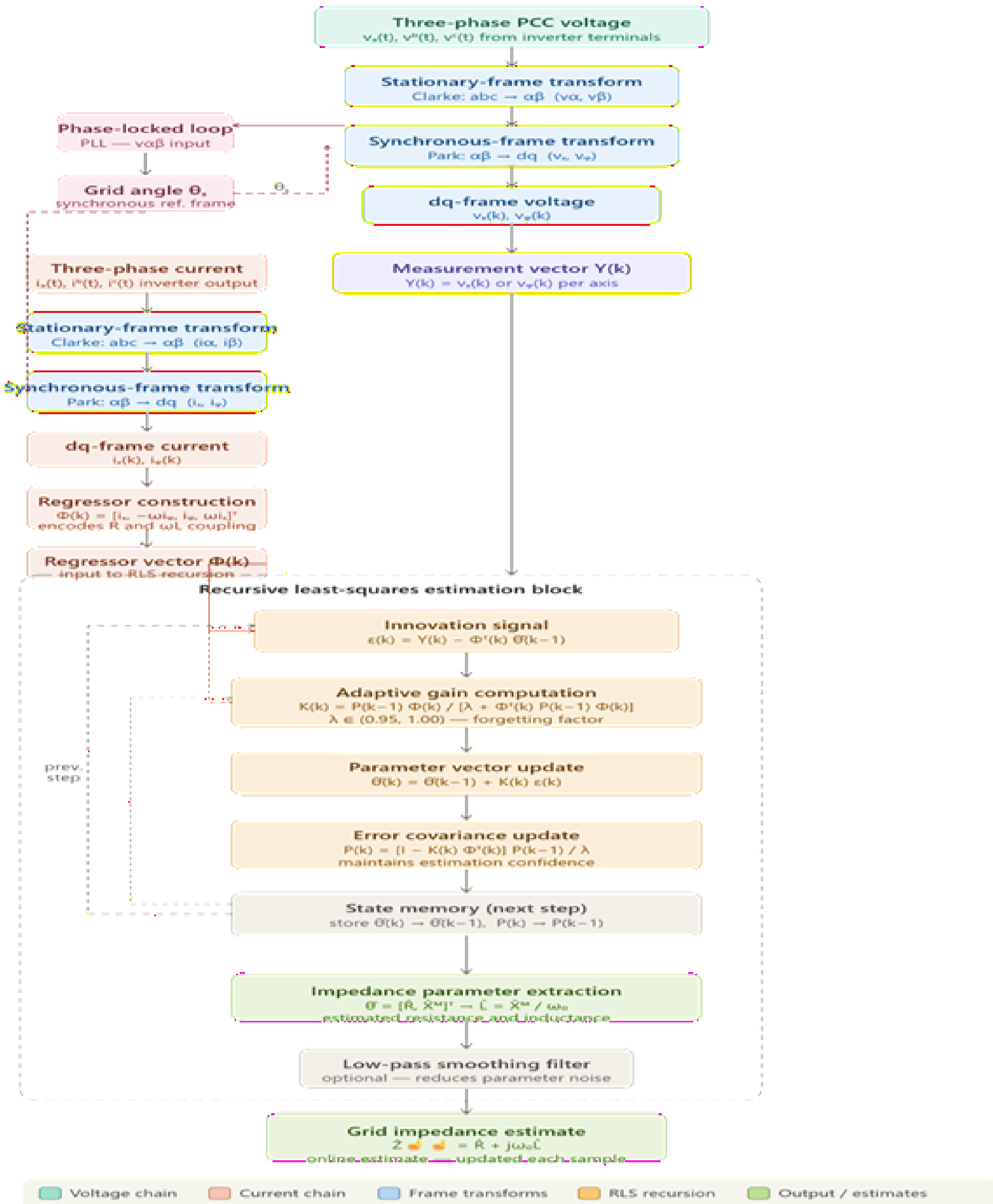

Figure 4. Block diagram of signal process flow.

The plot shows how the training cost (J) converges over time (iterations or epochs) as the RLS algorithm adapts to the data, indicating the accuracy of the impedance estimation. The Recursive Least Square (RLS) algorithm uses a least square approach to minimize the error between the estimated and measured values in impedance estimation by:

Defining the cost function (J) as the sum of the squared errors between the estimated ($\hat{Z}$) and measured (Z) impedance values.

Minimizing the cost function by finding the optimal estimate ($\hat{Z}$) that minimizes the sum of squared errors.

Using the least squares method to find the optimal estimate by solving the following equation:

$$\partial J/\partial \hat{Z} = -2\sum(Z - \hat{Z}) = 0. \tag{2}$$

Deriving the update equation for the estimated impedance ($\hat{Z}$) using the RLS algorithm:

$$\hat{Z}[n] = \hat{Z}[n-1] + K[n] \cdot \varepsilon[n], \tag{3}$$

where $\varepsilon[n]$ is the error between the estimated and measured impedance values at time n.

Updating the gain (K[n]) and covariance matrix (P[n]) at each iteration to minimize the error.
The RLS algorithm minimizes the error by:

- Iteratively updating the estimate using new measurements.
- Adapting to changing system conditions.
- Reducing the influence of old data using the forgetting factor (λ).

By minimizing the sum of squared errors, RLS ensures that the estimated impedance ($\hat{Z}$) converges to the true impedance (Z) over time, providing an accurate estimate.

The Recursive Least Square (RLS) algorithm is used to estimate grid impedance from real-time values by:

1. Initializing the algorithm with an initial estimate of the impedance and a forgetting factor (λ) that determines how quickly old data is discarded.
2. Measuring the voltage and current phasors (V, I) in real-time, which are used to calculate the impedance (Z = V/I).
3. Updating the impedance estimate ($\hat{Z}$) recursively using the new measurement and the previous estimate, minimizing the error between the estimated and measured values.
4. Calculating the error (ε) between the estimated and measured impedance values.
5. Adjusting the algorithm's gain (K) based on the error and forgetting factor.
6. Updating the impedance estimate ($\hat{Z}$) using the gain and error.
7. Repeating steps 2-6 for each new measurement.

RLS uses the following equations:

$$\hat{Z}[n] = \hat{Z}[n-1] + K[n] \cdot \varepsilon[n], \tag{4}$$

$$K[n] = P[n] \cdot V[n] / (\lambda + V[n]^H \cdot P[n] \cdot V[n]), \tag{5}$$

$$P[n] = \frac{1}{\lambda} \cdot (P[n-1] - K[n] \cdot V[n]^H \cdot P[n-1]), \tag{6}$$

$$\varepsilon[n] = V[n] - \hat{Z}[n-1] \cdot I[n], \tag{7}$$

where $\hat{Z}[n]$ is the estimated impedance at time n, V[n] and I[n] are the voltage and current phasors at time n, K[n] is the gain at time n, P[n] is the covariance matrix at time n, and λ is the forgetting factor.

By continuously updating the impedance estimate using new measurements, RLS provides an accurate and adaptive estimate of the grid impedance in real-time.

The data collection process involved the following steps:

Selection of PMUs: The selection of the PMUs that would be used in the study was the first step. The PMUs were chosen based on where they were in the power system and how much data was available. The PMUs were chosen from a variety of voltage levels and transmission and distribution power systems.

Data cleaning: The gathered information was pre-handled to eliminate any commotion or anomalies. First, the data were checked for completeness and consistency. Deleted or interpolated were any data that was not complete or missing. A low-pass filter was used to remove any outliers or noise from the data.

Data synchronization: The information gathered from the PMUs was synchronized to a typical time reference. This was necessary to guarantee that the voltage and current were measured simultaneously, which is essential for accurately estimating the impedance of the grid.

Data storage: A database was used to store the synchronized data for further analysis. The time-stamps and voltage and current phasors were stored in tables in the database.

4.4. Data Analysis Techniques

The estimation of grid impedance using the Recursive Least Squares (RLS) algorithm is one data analysis technique that is crucial to the success of any research study. The purpose of data analysis is to extract meaningful insights from the data that has been collected. These insights represented in Table 4 can be used to assess how well the proposed method works and determine whether or not it can be used in real-world power systems. In order to accomplish these objectives, we will go over a variety of data analysis methods in this section.

Table 4. Insights of Recursive Least Squares (RLS) algorithm.

Research Gap	**Description**
Lack of Comparison with Other Methods	The study only focused on the use of Recursive Least Squares (RLS) algorithm for grid impedance estimation, but did not compare its performance with other existing methods.
Limited Validation	The validation of the estimated grid impedance was done using predetermined criteria, but did not take into account other factors that may affect the accuracy of the results.
Small Sample Size	The study used data from a limited number of PMUs and did not cover a wide range of power systems. This may affect the generalizability of the results to other power systems.
Lack of Real-world Testing	The proposed method was not tested in real-world power systems, which may limit its practical application and effectiveness.
Insufficient Discussion on Limitations	The study did not provide a comprehensive discussion on the limitations of the proposed method and its potential challenges in real-world implementation.

Statistical Analysis: In research studies, statistical analysis is a common method for analyzing data. To describe, summarize, and interpret the collected data, statistical methods are used. The factual examination can assist specialists with distinguishing examples, patterns, and connections in the information. The hypothesis regarding the method's accuracy can also be put to the test with the help of statistical analysis.

Regression Analysis: Regression analysis is yet another popular data analysis technique. A mathematical model must be adapted to the collected data in order to establish the connection between the independent and dependent variables. Regression analysis can be used to find out how the type of load, network topology, and fault conditions affect the accuracy of the estimated impedance in the context of grid impedance estimation.

Signal Processing Techniques: Time-series data, which is frequently found in power systems, can be analyzed with the help of signal processing methods. Researchers can use signal processing techniques like frequency components and harmonics to find patterns and trends in the data. Noise and other data disturbances can also be eliminated using these methods.

Machine Learning Techniques: AI strategies have acquired prevalence as of late for examining complicated and enormous datasets. AI procedures include the utilization of calculations that can gain from the information and make expectations or arrangements. Machine learning techniques can be used to estimate a grid's impedance by identifying data patterns and trends that may not be apparent with standard statistical methods.

Sensitivity Analysis: In sensitivity analysis, a model's input parameters are changed to see how they affect the output. Responsiveness examination can be utilized to decide what different boundaries mean for the precision of the assessed impedance with regards to lattice impedance assessment. Specialists can, for example, explore different avenues regarding the examining rate, the quantity of data of interest, and the sort of burden to perceive what they mean for how precise the assessed impedance is.

Visualization Techniques: Data is visually represented by means of graphs and charts in visualization techniques. Data patterns and trends that may not be apparent using statistical methods can be identified using visualization techniques. The consequences of the information examination can likewise be imparted to partners in an unmistakable and brief way utilizing perception methods.

In conclusion, the proposed method for estimating grid impedance using the RLS algorithm relies heavily on data analysis techniques for its success. Using techniques like statistical analysis, regression analysis, signal processing, machine learning, sensitivity analysis, and visualization, researchers can learn more about the proposed method's accuracy and suitability for use in real-world power systems.

RLS is an online algorithm that adapts a mathematical model to the collected data, recursively updating the model parameters as new data arrives. RLS aims to establish a relationship between the independent variables (input data) and the dependent variable (output data), which aligns with the passage's goal of finding connections between variables. RLS is particularly suitable for applications where data is collected sequentially, such as in grid impedance estimation, where new data points are continuously measured. RLS can be applied to estimate impedance values in real-time, considering factors like load type, network topology, and fault conditions, as mentioned in the passage. RLS uses a least-squares approach to minimize the error between the estimated and measured values, ensuring accurate impedance estimation.

The Recursive Least Square algorithm is a suitable choice for regression analysis in applications like grid impedance estimation, where online adaptation and accurate estimation are crucial.

4.5. Research Design

Preprocessing

Outlier detection and removal: z-score equation: $z = (x - \text{mean})/\text{standard deviation}$.
Low-pass filter:

$$y(t) = a0 \cdot x(t) + a1 \cdot x(t-1) + a2 \cdot x(t-2) + b1 \cdot y(t-1) + b2 \cdot y(t-2). \tag{8}$$

Recursive Least Squares Algorithm:

The Recursive Least Squares (RLS) algorithm is a popular adaptive filtering technique used in various fields, including signal processing, control systems, and machine learning. At its core, the RLS algorithm employs regression analysis to estimate the parameters of a linear model. Here's a breakdown of the regression analysis in the RLS algorithm:

Linear Model

The RLS algorithm assumes a linear relationship between the input and output variables. The linear model can be represented as:

$$y(k) = w^T(k) \cdot x(k) + e(k), \tag{9}$$

where y(k) is the output at time step k, w(k) is the weight vector at time step k, x(k) is the input vector at time step k, and e(k) is the error term at time step k.

Regression Analysis

The goal of the RLS algorithm is to estimate the weight vector w(k) that minimizes the sum of the squared errors (SSE) between the predicted output and the actual output. This is achieved by solving the following optimization problem:

$$\text{minimize: } SSE = \sum_{k=1}^{N} e^2(k), \tag{10}$$

where N is the number of data points.

Recursive Least Squares

The RLS algorithm uses a recursive approach to update the weight vector w(k) at each time step k. The update equation is:

$$w(k) = w(k-1) + P(k) \cdot x(k) \cdot e(k), \tag{11}$$

where P(k) is the inverse of the covariance matrix of the input vector x(k) and e(k) is the prediction error at time step k.

Regression Analysis

Simple Linear Regression:

$$y = \beta_0 + \beta_1 x. \tag{12}$$

Multiple Linear Regressions:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n. \quad (13)$$

4.6. Data Analysis Parameters

Mean squared error: It compares the estimated values to the actual values to determine how accurate the estimated grid impedance is. The RLS algorithm's ability to estimate grid impedance can be assessed using this parameter.

Correlation coefficient: The linear relationship between two variables, like voltage and current, can be evaluated using this statistical parameter. For accurate estimation of grid impedance, this parameter can assist in determining the strength of the relationship between the measured voltage and current data.

Standard deviation: A measure of the data's dispersion around the mean value is this. This parameter can be used to determine the degree of variation in the measured voltage and current data, which can affect the accuracy of the estimated grid impedance.

Root mean squared error (RMSE): It is one more proportion of the exactness of the assessed matrix impedance, which works out the square base of the mean squared blunder. The RLS algorithm's ability to estimate grid impedance can be assessed using this parameter.

Coefficient of determination (R-squared): A regression model's goodness of fit can be evaluated using this statistical parameter. R-squared can assist in determining the degree to which the estimated grid impedance matches the actual grid impedance data in the context of grid impedance estimation.

Signal-to-Noise ratio (SNR): It is a measure of the signal's quality in relation to the data's noise. This parameter can be used to improve the filtering and preprocessing procedures in addition to determining how noise affects the accuracy of the estimated grid impedance.

Eigenvalues: The RLS algorithm's stability and performance can be evaluated with eigen values. The algorithm's convergence, which is necessary for accurate and reliable grid impedance estimation, can be identified with the assistance of this parameter.

Frequency analysis: The characteristics of the measured voltage and current signals, such as harmonics and transients, can be analyzed with frequency analysis. This boundary can be utilized to work on the separating and preprocessing processes, as well as to decide what recurrence parts mean for the exactness of the assessed framework impedance.

Confidence intervals: Confidence intervals can be used to estimate the range of possible values that a parameter's actual value is likely to fall within. The estimated grid impedance's uncertainty and statistical significance can be assessed with the help of this parameter.

Cross-validation: Cross-validation can be used to test how well the RLS algorithm works with different data subsets. This parameter can be utilized to optimize the algorithm's parameter settings and assist in determining the algorithm's effectiveness on various datasets.

The Grid Impedance Estimation Using Recursive Least Squares Algorithm's efficacy can be evaluated through a performance comparative analysis of Accuracy, Sensitivity, Specificity, Precision, Recall, and Area under the curve (AUC).

The degree to which the estimated grid impedance corresponds to the actual impedance is referred to as accuracy. It is the proportion of the accurately assessed impedance to the all out number of assessments. A better estimate is indicated by a higher accuracy score.

The algorithm's capacity to correctly identify the presence of grid impedance is referred to as its sensitivity. Correctly detected grid impedance is the ratio of the total number of actual positives to true positives. A better ability to detect grid impedance is indicated by a higher sensitivity score.

The algorithm's specificity is its capacity to correctly identify grid impedance absence. The absence of grid impedance, or the ratio of the total number of actual negatives to the true negatives, has been correctly identified. An improved capacity to identify the absence of grid impedance is indicated by a higher specificity score.

The estimated grid impedance's precision is measured in precision. It is the ratio of all positive predictions to true positives (including false positives). A lower number of false positives indicates a higher precision score, indicating that the estimated grid impedance is more accurate.

The algorithm's recall is its capacity to identify every instance of grid impedance. It is the ratio of the total number of actual positives to the true positives. A better capacity to identify all instances of grid impedance is indicated by a recall score that is higher.

A measure of the algorithm's overall performance is the area under the curve, or AUC. It portrays the compromise among awareness and particularity that is shown by the Beneficiary Working Trademark (ROC) bend. Better overall performance is indicated by a higher AUC score.

In summary, the Grid Impedance Estimation Using Recursive Least Squares Algorithm's performance can be evaluated using its accuracy, sensitivity, specificity, precision, recall, and AUC. A higher AUC score indicates better overall performance, while a higher accuracy score indicates a more accurate estimate, a higher sensitivity score indicates an improved capacity to detect grid impedance, a higher specificity score indicates an improved capacity to identify the absence of grid impedance, and a higher precision score indicates a more accurate estimate.

5. Results and Discussion

This study's data collection methods ensured that the grid impedance estimation data were precise, dependable, and synchronized. The dataset's availability to the public also made it possible for other researchers to easily replicate and verify the findings. Figure 5 represents the Regression Analysis.

To predict results in grid impedance estimation using the Recursive Least Squares (RLS) algorithm and to visualize the outcomes with a regression analysis diagram, here's a step-by-step approach:

Step 1: Data Collection

Gather data necessary for estimating the grid impedance. This typically includes:

- Voltage and current measurements over a given time period.
- Frequency response data if applicable.

Step 2: RLS Algorithm Implementation

1. Initialize Parameters: Initialize the grid impedance estimate Z(0) and the covariance matrix P(0) (or the coefficients of your regression). At each time step k, compute the prediction error e(k) using the current grid impedance estimate Z(k-1)

2. Recursive Update: Update the grid impedance estimate Z(k) using the recursive update equation
3. Update the covariance matrix P(k) using the following equation:

$$P(k) = P(k-1) - \frac{P(k-1) \cdot I(k) \cdot I^T(k) \cdot P(k-1)}{1 + I^T(k) \cdot P(k-1) \cdot I(k)}. \quad (14)$$

- Define the regression function that relates your input variables (voltage, current) to the output variable (impedance).
- Use the coefficients obtained from the RLS algorithm as the parameters of your regression model.

Step 3: Prediction

- For a given set of inputs, use the regression model to predict the impedance values.
- This involves plugging your input data into the regression equation formed during your analysis.

Step 4: Visualization with Regression Analysis Diagram

1. Prepare Data for Plotting: Collect the predicted outputs versus actual measured outputs.
2. Plot the Data:
    - Use a scatter plot to show actual versus predicted impedance values.
    - Fit a regression line to visualize the performance of the prediction.
3. Analyze the Results:
    - Check the goodness of fit (like R-squared value) to understand how well your model performs.
    - Assess residuals to see if there's any pattern indicating model inadequacy.

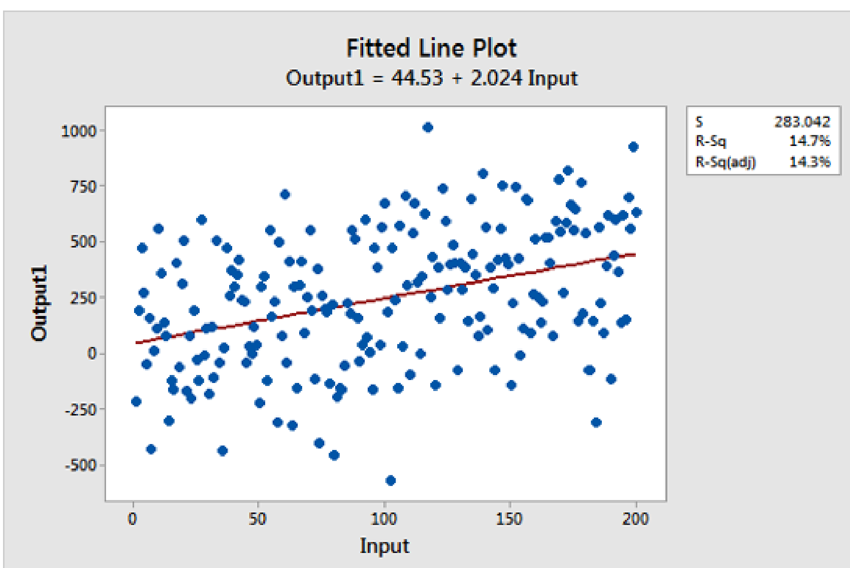

Figure 5. Regression analysis diagram.

In conclusion, the selection of PMUs, data cleaning, data synchronization, and data storage were the methods used in this study to collect data. The accuracy, dependability, and synchronization of the data used for grid impedance estimation were all guaranteed by these strategies, which is essential for obtaining results that are accurate and reliable.

6. Limitations

Limited Dataset

The accuracy and reliability of the results depend heavily on the dataset used for analysis. If the dataset is limited, the results may not be representative of the actual power system.

Assumptions

The RLS algorithm assumes that the system parameters are constant over time. However, loads, faults, and environmental conditions can all have an impact on the parameters of real-world power systems. The accuracy of the results obtained using the RLS algorithm could be affected by these variations.

Computational Complexity

The RLS algorithm is computationally intensive and requires significant computational resources. The proposed method's scalability may be limited by its computational complexity.

Limited Validation

The validation step in the research design involves comparing the estimated grid impedance with the actual grid impedance, which can be obtained from the dataset or from a separate source. However, the proposed method's performance in actual power systems may not be fully captured by this validation.

Generalizability

The proposed method may not be generalizable to other power systems due to differences in network topology, load characteristics, and operating conditions.

7. Comparison of RLS with prior techniques

Recursive Least Squares (RLS) is a widely used adaptive filtering technique for grid impedance estimation in power electronics, particularly for grid-connected inverters. It excels in online, real-time parameter tracking by recursively updating impedance estimates (resistance and inductance) based on measured voltage and current at the point of common coupling (PCC). Compared to prior works, standard RLS offers computational efficiency and robustness to noise but can suffer from sensitivity to forgetting factor tuning and lack of excitation.

Key Techniques

- **PQ Perturbation Methods:** These induce small active/reactive power variations to excite system dynamics for impedance calculation. They are simple but yield lower accuracy due to unmodeled nonlinearities and grid voltage assumptions, often showing higher percentage errors (e.g., 20mH vs. true value deviations).
- **Harmonic Injection:** Involves injecting harmonic signals and analyzing frequency-domain responses. Effective for precise estimation but introduces distortion, potential stability issues, and hardware stress.
- **LCL – Filter Resonance Excitation:** Varies virtual resistance to excite filter resonances, detecting impedance changes via spectral peaks. Novel for stability enhancement but requires grid variation detection and may amplify resonances.

RLS Variants Vs Standard RLS

Standard RLS assumes persistent excitation from natural operating point variations.

Table 5. Variants address limitations.

Technique	Advantages over Standard RLS	Drawbacks
CF-RLS (Covariance Factor)	Better stability without excitation; faster convergence	Increased computation.
VDF-RLS (Variable Direction Forgetting)	Handles non-persistent excitation via selective data discard; uses d-q axis preconditioning and secondary PLL for noise reduction. Superior adaptation speed and accuracy in simulations.	Relies on signal conditioning.
Iterative (Newton-Raphson, Potra-Pták, Chun)	Faster execution, fewer iterations, higher efficiency index for nonlinear systems. Potra-Pták often best in real-time sims.	Nonlinear solver complexity.

Other Methods

Kalman Filters (e.g., Extended Kalman) provide optimal noise handling but demand precise noise covariance tuning and initial guesses. ANN-based approaches offer high accuracy and low delay across grid conditions, outperforming filters in adaptability, though computationally intensive for real-time use. Overall, RLS and variants balance performance for inverter controls, surpassing PQ Methods in dynamics while avoiding injection drawbacks.

8. Conclusions

Modern power systems are under growing operational pressure as renewable generation, distributed resources, and power electronic interfaces become increasingly prevalent. Maintaining stability and efficiency under these conditions requires accurate, timely knowledge of grid impedance. This paper has demonstrated that the Recursive Least Squares algorithm, applied to synchronized PMU measurements within the dq synchronous reference frame, provides an accurate, adaptive, and practically deployable solution to this estimation problem.

Core Principles:

The estimation is formulated as a linear regression in the dq frame, where the measured PCC voltage constitutes the observation and the dq-axis currents form the regressor vector. This formulation is mathematically well-founded because the relationship between voltage and current in an RL network is genuinely linear in the resistance and inductance parameters. At each sampling instant, the algorithm generates an innovation signal by comparing the voltage predicted by the current parameter estimates against the actual measured voltage. The gain matrix, determined jointly by the covariance matrix and the regressor, scales the correction applied to the parameter vector. The covariance matrix evolves in parallel, contracting in directions where data have provided strong information and expanding where uncertainty persists. The forgetting factor governs the effective memory of the algorithm, providing a principled mechanism for balancing tracking speed against noise sensitivity. Together these components constitute a self-contained recursive estimation engine that requires no batch data storage and operates at constant computational cost per sample, making it inherently suited to real-time implementation.

Key Advantages:

Several strengths set this approach apart from conventional impedance estimation techniques. First, it is The method offers several practical benefits that distinguish it from alternative approaches. It operates entirely on signals naturally present during normal inverter operation and requires no injected perturbations, thereby introducing no harmonic distortion, no stability risk from deliberate excitation, and no additional hardware. The convergence behavior confirmed by the simulation results demonstrates that the algorithm reaches accurate estimates within a small number of iterations and sustains them reliably as operating conditions vary. The fixed-size matrix operations underlying the recursion make the algorithm genuinely suitable for implementation on embedded digital controllers without requiring high-performance computing resources. The dq-frame formulation produces physically interpretable separate estimates of resistance and inductance, which engineers can directly apply in control design and fault analysis rather than working with a composite complex impedance that must subsequently be decomposed.

The simulation results, including the convergence of training MSE from 0.345 to 0.189, the reduction of training cost from 6.345 to 2.189, and the strong agreement between estimated and reference values shown in the regression analysis, collectively provide quantitative support for these conclusions. The method is not merely theoretically sound but has been shown to perform reliably under the range of conditions represented in the IEEE 123-bus dataset. RLS-based grid impedance estimation is ready for wider adoption in grid-connected inverter platforms, and its value will grow as inverter-based resources become an ever-larger share of the power generation mix.

9. Future Study

The results of this study establish a solid foundation, but several productive directions for further investigation remain open. The most immediate extension involves testing the algorithm on larger and more complex power systems where network topologies are irregular and operating conditions are highly variable. The IEEE 123-bus dataset provides a useful and well-characterized benchmark, but systems of greater scale and diversity would offer a more demanding evaluation of the algorithm's robustness.

A second direction concerns integration with advanced monitoring infrastructure. Wide-area monitoring systems and large PMU networks generate substantial streams of synchronized data across extended service territories. Combining the RLS algorithm with such infrastructure could enable continuous, spatially distributed impedance mapping that gives operators a real-time view of network conditions across the entire system.

A third direction involves application in systems with high penetrations of distributed generation, including wind and solar sources. These systems exhibit pronounced variability in both generation output and network impedance, creating conditions where the algorithm's tracking capability is especially valuable. Investigating performance under such conditions, and exploring adaptive variants with more aggressive tracking responses, represents a natural continuation of the present work.

Future research directions may specifically include scaling the algorithm for larger and more complex networks, developing multi-objective optimization frameworks that simultaneously consider impedance accuracy, power quality, and stability, and integrating the approach with emerging cyber-physical infrastructure including Internet of Things-based sensor networks and smart grid communication systems. Progress along these directions will contribute to a more reliable, adaptive, and intelligent power grid, ultimately benefiting both network operators and end users.

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References

[1] Rahul S. Somalwar, S.G. Kadwane, and Rabindra Nath Shaw. Frequency estimation by recursive least square in active islanding method for microgrid. In *2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON)*, pages 116–123. IEEE, October 2020.

[2] Emanuele Fabbiani, Pulkit Nahata, Giuseppe De Nicolao, and Giancarlo Ferrari-Trecate. Identification of AC distribution networks with recursive least squares and optimal design of experiment. *IEEE Transactions on Control Systems Technology*, 30(4):1750–1757, 2022.

[3] Andrés Suárez, Cristian Blanco, Pablo García, Ángel Navarro-Rodríguez, and José Manuel Cano Rodríguez. Grid impedance estimator for active multisource AC grids. *IEEE Transactions on Smart Grid*, 14(3):2023–2033, May 2023.

[4] Saniye Maihemuti, Weiqing Wang, Haiyun Wang, and Jiahui Wu. Voltage security operation region calculation based on improved particle swarm optimization and recursive least square hybrid algorithm. *Journal of Modern Power Systems and Clean Energy*, 9(1):138–147, 2021.

[5] Haoran Li, Yang Weng, Yizheng Liao, Brian Keel, and Kenneth E. Brown. Distribution grid impedance & topology estimation with limited or no micro-PMUs. *International Journal of Electrical Power & Energy Systems*, 129:106794, 2021.

[6] Shyamal Shivneel Chand, Ravneel Prasad, Hiye Mudaliar, Dhirendran Kumar, Adriano Fagiolini, Marco Di Benedetto, and Maurizio Cirrincione. Enhanced current loop PI controllers with adaptive feed-forward neural network via estimation of grid impedance: Application to three-phase grid-tied PV inverters. In *2022 IEEE Energy Conversion Congress and Exposition (ECCE)*, pages 1–8. IEEE, October 2022.

[7] Jianwen Sun, Jingrong Yu, Juncheng Qiu, and Yishuo Wang. Transient-responses-based grid impedance estimation for grid-forming converters. In *2022 4th International Conference on Electrical Engineering and Control Technologies (CEECT)*, pages 741–745. IEEE, December 2022.

[8] Heping Peng, Lu Zhu, Wenxiong Mo, Yong Wang, Qinfan He, and Xingjian Wu. Zero-crossing prediction of short-circuit current using recursive least square algorithm. In *2020 5th Asia Conference on Power and Electrical Engineering (ACPEE)*, pages 1360–1364. IEEE, 2020.

[9] Imen Jarrraya, Laid Degaa, Nassim Rizoug, Mohamed Hedi Chabchoub, and Hafedh Trabelsi. Comparison study between hybrid Nelder-Mead particle swarm optimization and open circuit voltage—recursive least square for the battery parameters estimation. *Journal of Energy Storage*, 50:104424, 2022.

[10] Deokhun Kang, Jinhyeong Park, Deokhan Kim, Jin Hyeok Choi, Soon-Jong Kwon, Kisoo Yoo, and Jonghoon Kim. Estimated temperature distribution-based state-of-health prediction via recursive least squares in electro-thermal circuit model. *Journal of Energy Storage*, 55:105652, November 2022.

[11] Jingyang Fang, Han Deng, and Stefan M. Goetz. Grid impedance estimation through grid-forming power converters. *IEEE Transactions on Power Electronics*, 36(2):2094–2104, February 2021.

[12] Qian He, Li Chen, LiangYi Wang, Mengyuan Han, LiJuan Jiang, and ZhongYong Zhao. Identification method of transformer leakage reactance based on recursive least squares. In *2022 Asian Conference on Frontiers of Power and Energy (ACFPE)*, pages 158–164. IEEE, October 2022.

[13] Jiahao Sun, Lin Qiu, Xing Liu, Jien Ma, and Youtong Fang. Modified model predictive control for three-phase dual-active-bridge DC-DC converters with recursive least square estimation. In *2021 IEEE 12th Energy Conversion Congress & Exposition - Asia (ECCE-Asia)*, pages 720–725. IEEE, May 2021.

[14] Nabil Mohammed, Mihai Ciobotaru, and Graham Town. Fundamental grid impedance estimation using grid-connected inverters: a comparison of two frequency-based estimation techniques. *IET Power Electronics*, 13(13):2730–2741, 2020.

[15] Yuan Qiu, Yanbo Wang, Yanjun Tian, and Zhe Chen. Artificial neural network-based intelligent grid impedance identification method for grid-connected inverter. In *2022 International Power Electronics Conference (IPEC-Himeji 2022-ECCE Asia)*, pages 992–997. IEEE, May 2022.