ADVANCED CHARACTERIZATION OF POWER SYSTEM HARMOICS USING MUSIC ALGORITHM ON NON-STATONARY WAVEFORMS

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Abstract - Maintaining power quality in modern power systems is crucial, as the integration of renewable energy sources and the rise of non-linear loads have resulted in intricate harmonic distortions. Ordinary methods based on Fourier series, like the Fast Fourier Transform (FFT), are frequently used for harmonic analysis; however, they often struggle to accurately analyze non-stationary signals, which are commonly observed due to system disturbances and variations. This research investigates the Multiple Signal Classification (MUSIC) algorithm as a more advanced option for harmonic analysis in power systems. The high-resolution frequency estimation provided by MUSIC allows for precise identification of harmonic amplitudes and phases, even in the presence of noise and fluctuations in the fundamental frequency. In this study, synthetic non-stationary waveforms that simulate actual conditions at the Point of Common Coupling (PCC) are examined to demonstrate MUSIC's capability to identify harmonics accurately where traditional FFT-based methods fail. Findings from simulations indicate that MUSIC not only provides enhanced accuracy in harmonic characterization but also exhibits resilience under non-stationary conditions, making it particularly effective for real-time power quality monitoring. This research emphasizes MUSIC as an important progress in harmonic analysis, presenting a valuable resource for enhancing power system reliability in dynamic settings.

Keywords: Power quality, Harmonic analysis, MUSIC algorithm, Fast Furrier Transform, Signal processing, Time-varying systems

1. INTRODUCTION

1.1. Background

Harmonics in electrical power systems originate from multiple sources, including non-linear loads, power electronic converters such as inverters and rectifiers, as well as a range of contemporary electrical appliances. These harmonics lead to serious problems, such as equipment overheating, heightened losses in power transmission and distribution, incorrect functioning of protective relays, and disruptions to communication systems. As renewable energy sources become more integrated and advanced electronic devices are used more widely, the demand for efficient power quality management and harmonic distortion reduction is becoming increasingly critical. Power systems are encountering greater complexity when it comes to sustaining stability and performance as levels of harmonic distortion rise [1-2]. Recent studies indicate that escalating harmonic distortion levels, influenced by modern energy technologies such as solar photovoltaic systems, electric vehicle chargers, and wind energy conversion systems, present further challenges for ensuring grid stability [3]. Harmonic distortion can disrupt protection systems and control algorithms, requiring sophisticated detection and mitigation techniques to maintain the integrity of the power grid [4].

1.2. Literature Review

Conventional techniques, like the Fast-Fourier-Transform (FFT), have been widely adopted to characterize harmonics due to their ease of use. FFT is a popular method for analyzing frequency components in signals, including harmonics in power systems. However, FFT has certain limitations, especially when dealing with non-stationary signals or closely spaced harmonic frequencies [5]. These limitations often result in inaccurate harmonic characterization, which can hinder the effectiveness of mitigation techniques.

An alternative to FFT, the Multiple Signal Classification (MUSIC) algorithm, originally developed for radar and sonar applications, has been shown to offer high-resolution frequency estimation [6]. MUSIC effectively separates signals into signal and noise subspaces, making it capable of identifying and quantifying harmonic components even in noisy or non-stationary conditions [7].

Research studies have demonstrated the superiority of the MUSIC algorithm for harmonic identification and characterization in both steady-state and transient conditions [8]. It has shown particular effectiveness in power quality monitoring applications, where it outperforms conventional techniques in dynamic and time-varying power systems [9]. The algorithm's ability to handle noisy signals while providing accurate harmonic detection makes it a suitable choice for modern power systems with complex harmonic behaviors.

While the Fast-Fourier-Transform (FFT) is the most commonly used technique for harmonic analysis, alternative approaches such as Wavelet Transform, Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), and Singular Value Decomposition (SVD) have also been applied in power system harmonic characterization.

a) Wavelet Transform (WT)

Wavelet-based techniques provide time-frequency resolution, making them suitable for analyzing transient signals and non-stationary waveforms. However, WT suffers from a lack of precision in frequency resolution, particularly when dealing with harmonics that are closely spaced. Additionally, selecting the optimal mother wavelet and scales can be computationally intensive, and performance can degrade in noisy conditions [10].

b) Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT)

ESPRIT is a subspace-based algorithm, similar to MUSIC, used for frequency estimation. While ESPRIT can provide high-resolution estimation with lower computational complexity, it assumes that the number of harmonics is known a priori. This limitation can be problematic when harmonic orders vary dynamically, leading to inaccurate results. Moreover, ESPRIT's performance in noisy environments is generally inferior to MUSIC [11].

c) Singular Value Decomposition (SVD)

SVD is often used for signal decomposition and noise reduction, particularly in the presence of higher noise levels. However, SVD is sensitive to signal scaling and cannot directly provide frequency information without additional computational steps. In comparison, MUSIC offers direct frequency estimation and better noise robustness, especially in dynamic conditions [12].

Despite their advantages, these methods face limitations in the precision and accuracy of harmonic estimation, especially in noisy and dynamic environments. In contrast, the MUSIC algorithm excels in separating signal from noise subspaces, making it more effective for harmonic detection and characterization in modern power systems. MUSIC has demonstrated superior performance in identifying closely spaced harmonic frequencies and can operate effectively even in highly noisy conditions, making it a strong candidate for power quality monitoring in the presence of renewable energy resources [13].

1.3. Research Gap and Motivation

The transition to renewable energy sources in power systems introduces complexities related to power quality, particularly in terms of harmonics generated by non-linear loads and inverter-based resources. Existing harmonic analysis techniques often fall short in accurately detecting and quantifying these harmonics in real-time, especially under fluctuating conditions common in operational power grids [14].

While several methods, such as Fourier Transform and wavelet analysis, have been widely used for harmonic detection, they lack the resolution and adaptability required for modern grid environments that experience intermittent energy generation and dynamic load variations.

The MUSIC (Multiple Signal Classification) algorithm presents a promising alternative due to its high-resolution capabilities in estimating the frequency content of signals. However, its application in power systems, particularly for harmonic analysis in environments with significant renewable integration, remains underexplored. The motivation for this research stems from the necessity to validate and enhance the applicability of the MUSIC algorithm in dynamic power system environments, thus addressing the pressing need for robust, real-time harmonic monitoring solutions [15].

1.4. Challenge

The primary challenge addressed in this research is the accurate characterization of harmonics in non-stationary environments, such as those observed in power systems integrating renewable energy sources. Conventional techniques like FFT struggle to differentiate between closely spaced harmonic frequencies and perform poorly in noisy conditions [16]. The complexity of modern power systems, with their dynamic and time-varying nature, exacerbates this issue. Furthermore, the increasing number of power electronics and inverter-based resources creates additional harmonic distortion, requiring more precise and effective analytical methods to ensure the stability and reliability of the power grid [17].

1.5. Contribution

This paper presents a novel application of the MUSIC algorithm for high-resolution harmonic analysis in power systems, with a focus on non-stationary synthetic waveforms representing realistic conditions at the Point of Common Coupling (PCC). The key contribution lies in demonstrating the algorithm's superior accuracy and resolution in harmonic characterization, significantly outperforming conventional methods like FFT. This work not only expands the understanding of the MUSIC algorithm's efficacy in noisy and dynamic power system environments but also underscores its potential to enhance power quality monitoring and mitigation strategies critical to modern grids. Additionally, this study establishes a robust framework for further research, pinpointing strategic areas for future exploration. By advancing harmonic analysis methodologies, this research supports the evolution of more reliable and efficient power quality monitoring systems, essential for the effective integration of renewable energy sources into power grids. [18-19].

1.6. Paper Organization

The remainder of this paper is structured as follows: Section 2 presents the methodology, detailing the steps involved in generating a realistic synthetic dataset and the mathematical formulation of the MUSIC algorithm.

Section 3 presents the simulation results, where the effectiveness of the algorithm is demonstrated through various case studies. Section 4 discusses the results, emphasizing the advantages of the MUSIC algorithm over conventional techniques. Finally, Section 5 concludes the paper by summarizing the key findings and suggesting future research directions for enhancing harmonic analysis in power systems.

2. METHODOLOGY

2.1. Synthetic Data Generation

The development and evaluation of harmonic analysis techniques is significantly hindered by the lack of publicly available datasets containing power systems waveforms. In order to solve this problem, we created synthetic waveforms that replicated the characteristics commonly seen at the point of common coupling (PCC) in power systems and simulation outputs from software like Simulink. By using these synthetic waveforms as substitutes for actual waveforms, we are able to thoroughly test our suggested approach. The synthetic dataset replicates a range of operation modes and transient events. To mimic the complexity seen in real power systems waveforms, harmonic components are introduced to each waveform with various amplitudes and phases.

2.1.1. Fourier series Representation of Power System Waveforms

The Fourier series representation is a mathematical technique used to decompose periodic signals into their constituent sinusoidal components or harmonics. In power systems, waveforms are typically complex signals containing both the fundamental frequency and harmonics. Accurately understanding the amplitude and phase of each harmonic is essential for modeling and analyzing waveform behavior. The Fourier series representation of a power system waveform x(t) can be expressed as: [20]

$$x(t) = A_0 + \sum_{k=1}^{N} A_k \sin\left(2\pi k f_{fund} t + \phi_k\right) \qquad (2.1)$$

Where f_{fund} is the fundamental frequency of the signal, A_k and ϕ_k are the amplitude and phase of the k-th harmonic component, N is the highest harmonic number considered, and A_0 represents the DC component. Using trigonometric identities, the expression given in equation (2.1) can be rewritten as:

$$x(t) = A_0 + \sum_{k=1}^{N}\left[a_k \sin\left(2\pi k f_{fund} t\right) + b_k \cos\left(2\pi k f_{fund} t\right)\right] \qquad (2.2)$$

Where $a_k = A_k \cos(\phi_k)$, and $b_k = A_k \sin(\phi_k)$, represent the sine and cosine harmonic coefficients, respectively. The amplitude A_k and phase ϕ_k of the k-th harmonic are calculated as:

$$A_k = \sqrt{a_k^2 + b_k^2} \qquad (2.3)$$

$$\phi_k = tan^{-1}\left(\frac{b_k}{a_k}\right) \qquad (2.4)$$

2.1.2. Harmonics Coefficients Scaling

In this study, harmonic amplitude scaling factors are selected to reflect typical harmonic amplitudes observed in real power systems, creating a realistic waveform model. The amplitude of the fundamental component A_1 varies between 0.7 and 1.1 per unit (pu):

$$A_1 \in [0.7,\ 1.1] \qquad (2.5)$$

Higher harmonics are generated as percentages of A_1, following real power system observations.

a) Generation of Random Harmonic Amplitude Coefficients

Random amplitude coefficients for the sine and cosine terms of the fundamental frequency and its harmonics are generated within these ranges to construct the Fourier series representation. This variability simulates the stochastic nature of harmonic disturbances in actual power networks.

For the fundamental waveform, the amplitude coefficients are:

$$a_1 = \frac{0.7 + \text{ran}\ () \cdot 0.4}{\sqrt{2}} \qquad (2.6)$$

$$b_1 = \frac{0.7 + \text{rand}() \cdot 0.4}{\sqrt{2}} \qquad (2.7)$$

For higher harmonics (k = 2 to N), the coefficients are given by:

$$a_k = 0.001 + \ \text{rand}() \cdot (sf(k) \cdot a_1 - 0.001) \qquad (2.8)$$

$$b_k = 0.001 + \ \text{rand}() \cdot (sf(k) \cdot b_1 - 0.001) \qquad (2.9)$$

Where, rand() generates a random number between 0 and 1, and sf(k) is the scaling factor for the k-th harmonic:

$$sf = [0.3, 0.5, 0.2, 0.8, 0.2, 0.5, 0.1, 0.2, 0.1, 0.2, 0.1, 0.2, 0.1, 0.2] \qquad (2.10)$$

2.1.3. Decaying DC Component and Noise

A decaying DC component and Gaussian noise are added to enhance realism, simulating transient effects and measurement noise. The expression for these disturbances is:

$$0.5e^{-5t} + 0.05 \cdot randn(N_s) \qquad (2.11)$$

Where N_s is the number of samples, and randn() generates standard normal random numbers.

2.1.4. Fundamental Frequency Variations

To simulate realistic conditions, the fundamental frequency is nominally set to 50 Hz and randomly varied within 49.5 to 50.5 Hz every 256 samples. The frequency for each sample n is:

$$f_{fund} = \begin{cases} 49.5 + \text{rand}() & \textbf{\textit{if}}\ mod(n-1,\ 256) < 8\ \textbf{\textit{and}}\ mod(n,8) = 1 \\ no\ change & \textbf{\textit{if}}\ mod(n-1,\ 256) < 8\ \textbf{\textit{and}}\ mod(n,8) \neq 1 \\ 50 & otherwise \end{cases} \tag{2.12}$$

2.1.5. Addition of Various Noise Types

In this study, we conducted a detailed comparison of the performance of the MUSIC algorithm and the Fast Fourier Transform (FFT) in the presence of different noise types. The goal is to evaluate the robustness and accuracy of both methods under realistic noise conditions, including white Gaussian noise, colored noise (pink noise), and impulsive noise, in addition to a decaying DC component combined with Gaussian noise described above.
Both FFT and MUSIC were applied to the same synthetic datasets containing harmonic signals with added noise, allowing for a direct comparison of their ability to estimate the harmonic contents.

a) White Gaussian Noise (WGN)`

White Gaussian noise is characterized by a constant power spectral density across all frequencies [20]. Its mathematical representation can be expressed as:

$$n_{WGN}(t) = \sigma_n \cdot z(t) \tag{2.13}$$

Where z(t) is a zero-mean Gaussian random variable with unit variance, and σ_n is the standard deviation of the noise, determining the noise power. In our tests, we set σ_n such that the Signal-to-Noise Ratio (SNR) was 20 dB.

b) Colored Noise (Pink Noise)

Pink noise, also known as 1/f noise [21] has a power spectral density that decreases with increasing frequency. Its power spectral density can be mathematically expressed as:

$$S(f) = \frac{K}{f^b} \tag{2.14}$$

Where *K* is a constant and *b* is typically set to 1. The time-domain representation can be generated using techniques like filtering white noise through a low-pass filter or using algorithms like the Voss-McCartney method. We used MATLAB's dsp.ColoredNoise () function to generate pink noise.

c) Impulsive Noise

Impulsive noise consists of sporadic high-amplitude spikes [22]. It can be mathematically represented as:

$$n_{impulsive}(t) = \sum_{k=1}^{N_P} A_k \cdot \delta(t - t_k) \tag{2.15}$$

Where A_k represents the amplitude of the k-th impulse, t_k is the time at which the impulse occurs, N_P the number of impulses, and δ(t)\ is the Dirac delta function. For our tests, we introduced 10 random impulses within the signal.
The synthetic waveform *x(t)* becomes:

$$x(t) = \sum_{k=1}^{N} [a_k \sin(2\pi k f_{fund} t) + b_k \cos(2\pi k f_{fund} t)] + 0.5e^{-5t} + 0.05 \cdot randn(N_s) + (WGN\ or\ PINK, or\ IMPULSIVE) \tag{2.16}$$

2.1.6. Furrier Coefficient Calculation

The actual values of the harmonic amplitude and phase are calculated from the generated waveform x(t) in equation (2.16), based on the integral expressions for Fourier coefficients:

$$a_k = \frac{2}{T} \int_{t_0}^{t_0+T} x(t) \cos(2\pi k f_{fund} t) dt \tag{2.17}$$

$$b_k = \frac{2}{T} \int_{t_0}^{t_0+T} x(t) \sin(2\pi k f_{fund} t) dt \tag{2.18}$$

Where *T* is the time period of the waveform. The expressions in (2.17) and (2.18) are approximated in MATLAB as:

$$a_k = 2 f_{fund} \cdot \boldsymbol{trapz}(t, x(t) \cdot \cos(2\pi k f_{fund} t)) \tag{2.19}$$

$$b_k = 2 f_{fund} \cdot \boldsymbol{trapz}(t, x(t) \cdot \sin(2\pi k f_{fund} t)) \tag{2.20}$$

2.2. The MUSIC Algorithm

The MUSIC algorithm is a subspace-based method used for frequency estimation, [16], [18]. It operates by decomposing the signal into signal and noise subspaces, allowing precise identification of signal frequencies.

2.2.1. Mathematical Formulation

Let $x(t)$ be a discrete-time signal sampled at N_s time points. The signal is assumed to be composed of N sinusoids corrupted by noise and non-stationarity similar to the synthetic waveform previously generated, equation (2.16).

a) Formation of Autocorrelation Matrix

First, we construct the autocorrelation matrix R from the signal samples:

$$R = \frac{1}{N_s} \sum_{t=1}^{N_s} x(t) x(t)^H \tag{2.21}$$

Where $x(t)^H$ is the Hermitian transpose of $x(t)$.

b) Eigenvalue Decomposition

Then we perform eigenvalue decomposition on R:

$$R = E\Lambda E^H \quad (2.22)$$

Where Λ is a diagonal matrix of eigenvalues and E is the matrix of eigenvectors.

2.2.2. Frequency Estimation

After eigenvalue decomposition is performed, we separate the eigenvalues into signal and noise subspaces. The smallest $N_s -$ N eigenvalues correspond to the noise subspace. Let *En* be the eigenvectors associated with these smallest eigenvalues.
The pseudo-spectrum *P(f)* is given by:

$$P(f) = \frac{1}{\sum_{i=1}^{N_S-N} \left|\boldsymbol{a}(f)^H E_n(:,i)\right|^2} \quad (2.23)$$

Where $\boldsymbol{a}(f) = [1, e^{-j2\pi f t_1}, e^{-j2\pi f t_2}, \ldots, e^{-j2\pi f t_{N_S-1}}]^T$ is the steering vector at frequency f and $E_n(:,i)$ i-th column of E_n. The peaks in the pseudo-spectrum *P(f)* correspond to the harmonic frequencies f_k.

2.2.3. Amplitude and Phase Estimation

Once the frequencies are estimated, the amplitudes and phases of the harmonic components can be determined by fitting the model directly to the observed signal. The amplitudes and phases can be estimated using least-squares fitting or other parametric methods. Specifically, we form a matrix M where each column consists of $\cos(\omega_k t)$ and $\sin(\omega_k t)$ components

a) *Formation of Matrix M with Sine and Cosine Components*

Given a signal x(t), a set of frequencies $\{\omega_k\}$, k =1 to N, and a regularization term λ, we start by forming the matrix M using cosine and sine terms as follows:.

$$M = \begin{bmatrix} \cos(\omega_1 t_1) & \sin(\omega_1 t_1) & \cdots & \cos(\omega_N t_1) & \sin(\omega_N t_1) \\ \cos(\omega_1 t_2) & \sin(\omega_1 t_2) & \cdots & \cos(\omega_N t_2) & \sin(\omega_N t_2) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \cos(\omega_1 t_{N_s}) & \sin(\omega_1 t_{N_s}) & \cdots & \cos(\omega_N t_{N_s}) & \sin(\omega_N t_{N_s}) \end{bmatrix} \quad (2.24)$$

Where $\{t_1, t_2, \ldots, t_{N_s}\}$, are time samples.

b) Regularized Least Squares Solution to Estimate Coefficients

To estimate the coefficients, we solve the linear system $\mathbf{Mp} = \mathbf{x}$ where **p** contains the amplitude and phase information. The regularization term, $\lambda = 1 \times 10^{-7}$ helps to prevent overfitting.
The solution is given by:

$$p = (M^T M + \lambda I)^{-1} M^T \boldsymbol{x} \quad (2.25)$$

Where $\boldsymbol{x} = \left[x(t_1), x(t_2), \ldots, x(t_{N_s})\right]^T$ is the signal vector, and **I** the identity matrix.

c) Calculation of Amplitude and Phase from the Coefficients

Once the coefficient vector **p** is estimated, we can determine the amplitude A_k and phase ϕk for each frequency fk, using:.

$$a_k = \mathbf{p}(2k-1) \quad (2.26)$$

$$b_k = \mathbf{p}(2k) \quad (2.27)$$

3. RESULTS AND DISCUSSION

This section presents the results of applying the MUSIC and FFT algorithms to estimate harmonic amplitudes and phases across different noise environments. The analysis examines the impact of noise, algorithm accuracy, mean absolute error (MAE) trend, and computational efficiency.

3.1. Impact of Noise Environments on Harmonic Estimation

Figures 3.1, 3.2, and 3.3 display simulated waveforms with White Gaussian Noise (WGN), Pink Noise, and Impulsive Noise, respectively, to illustrate the nature of disturbances each noise type introduces.

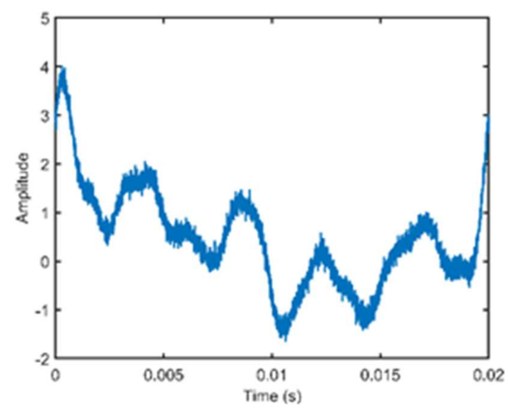

Fig. 3.1. Waveform with White Gaussian Noise (WGN)

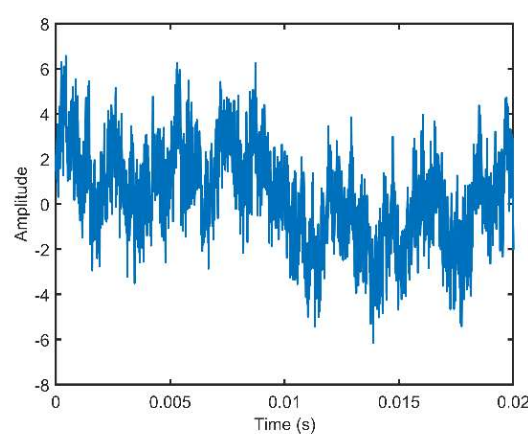

Fig.3.2. Waveform with Pink Noise

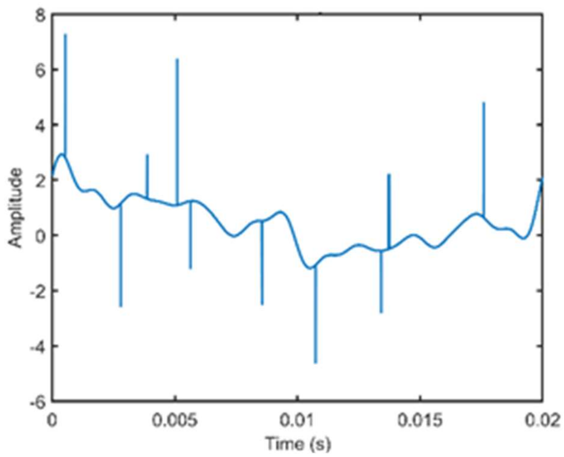

Fig.3.3 Waveform with Impulsive Noise

Each noise type affects harmonic estimation differently, providing a basis for evaluating the accuracy of the MUSIC and FFT algorithms.

3.2. Harmonic Estimation Accuracy Comparison by Noise Type

To comprehensively evaluate the performance of MUSIC and FFT under each noise condition, we present separate analyses for harmonic amplitude and phase estimation accuracy in WGN, Pink Noise, and Impulsive Noise environments.

a) Harmonic Estimation Accuracy in White Gaussian Noise

Figures 3.4 and 3.5 present the harmonic amplitude and phase estimation accuracy for both algorithms under WGN conditions.

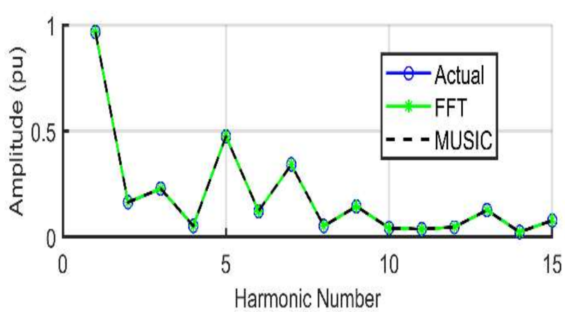

Fig.3.4. Harmonic Amplitude Estimation with WGN

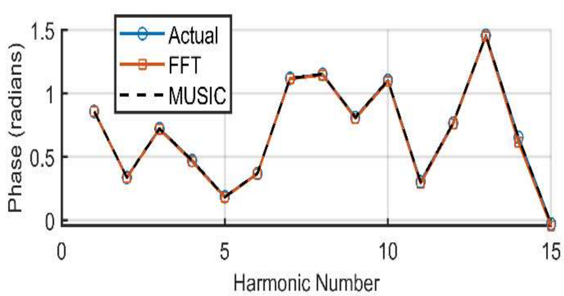

Fig.3.5. Harmonic Phase Estimation with WGN

In this low-interference environment, MUSIC displays higher accuracy, with smaller deviations from actual values compared to FFT, though both algorithms perform reasonably well due to the relatively low noise complexity.

b) Harmonic Estimation Accuracy in Pink Noise

Figures 3.6 and 3.7 depict the harmonic amplitude and phase estimation accuracy for both algorithms in Pink Noise conditions, which introduce frequency-dependent challenges.

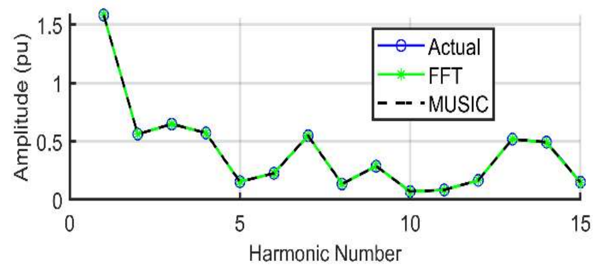

Fig.3.6. Harmonic Amplitude Estimation with Pink Noise

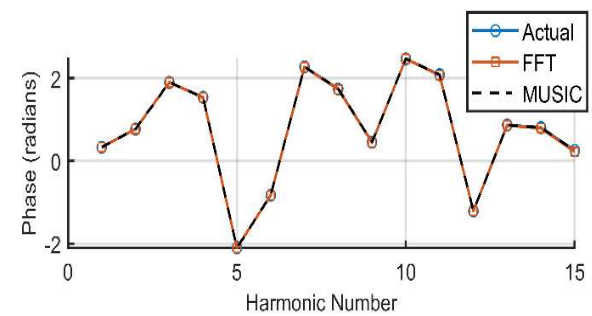

Fig.3.7. Harmonic Phase Estimation with Pink Noise

Pink Noise affects FFT's estimation accuracy, particularly for phase estimation in higher-order harmonics. The MUSIC algorithm, however, maintains higher accuracy, showcasing its robustness under frequency-dependent noise.

c) Harmonic Estimation Accuracy in Impulsive Noise

Figures 3.8 and 3.9 illustrate the harmonic amplitude and phase estimation accuracy under Impulsive Noise, which poses the most severe challenge.

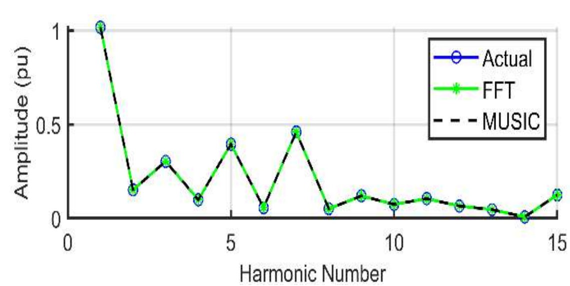

Fig.3.8. Harmonic Amplitude Estimation with Impulsive Noise

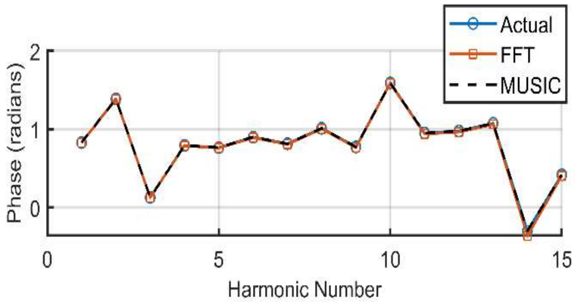

Fig.3.9. Harmonic Phase Estimation with Impulsive Noise

In this environment, FFT accuracy significantly deteriorates, especially for higher harmonics, while MUSIC demonstrates resilience, achieving substantially closer estimates to actual values even in the presence of high-amplitude noise peaks.

3.3. Mean Absolute Error (MAE) Analysis by Noise Type

Figures 3.10 and 3.11 provide a comparative analysis of Mean Absolute Error (MAE) for amplitude and phase estimation under each noise type.

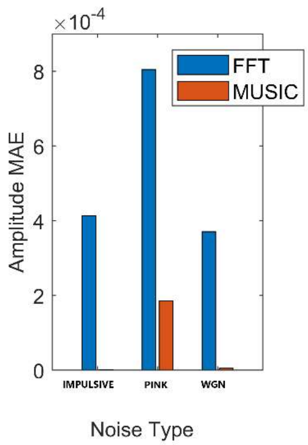

Fig.3.10. MAE for Amplitude Estimation across Noise Types

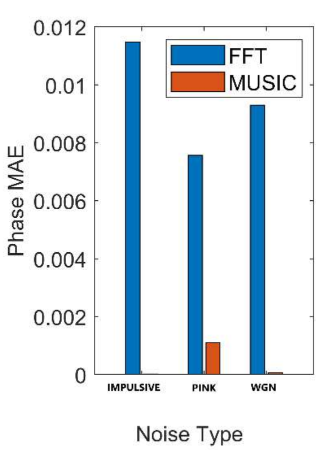

Fig.3.11. MAE for Phase Estimation across Noise Types

The MAE analysis reveals that the MUSIC algorithm consistently yields lower MAE across noise environments, with significant advantages over FFT in Pink and Impulsive Noise conditions. These results emphasize MUSIC's suitability for applications demanding high accuracy in noisy environments.

3.4. Algorithm Execution Time

Despite the superior accuracy of the MUSIC algorithm, it comes at the cost of increased computational time. Table 3.1 compares the execution times of the FFT and MUSIC algorithms for the impulsive noise scenario. As expected, the FFT algorithm was much faster, with an elapsed time of 5.810E-03 seconds compared to the 3.003E-01 seconds for MUSIC. The trade-off between accuracy and computational efficiency is evident, with the FFT being more suitable for real-time applications where speed is a priority, while MUSIC is better suited for scenarios requiring high-precision harmonic analysis.

Table 3.1. Elapsed Time Comparison for Impulsive Noise Scenario

FFT (seconds)	MUSIC (seconds)
5.810E-03	3.003E-01

4. DISCUSSION

The comparative analysis of the FFT and MUSIC algorithms demonstrates their respective strengths and weaknesses in harmonic amplitude and phase estimation within power systems under varying noise conditions. These results underscore the importance of selecting the appropriate algorithm based on specific application requirements. While FFT remains a reliable choice for scenarios where computational efficiency is prioritized, the MUSIC algorithm is more appropriate for situations necessitating exact amplitude and phase estimations. Future research could focus on developing hybrid approaches or optimizations that combine the strengths of both FFT and MUSIC, potentially offering a balanced solution for harmonic analysis in power systems.

4.1. Practical Implementation and Integration of MUSIC with Existing Power Quality Monitoring Systems and Standards

Integrating the MUSIC algorithm into existing power quality monitoring systems offers promising potential for enhancing the accuracy and resolution of harmonic detection in modern power grids. However, practical implementation requires addressing key challenges, such as ensuring compatibility with industry standards, optimizing computational efficiency, and integrating real-time data processing.

a) Integration with Existing Standards

Power quality monitoring systems in most regions are governed by international standards, such as IEEE 519

[18], IEC 61000-4-7 [23], and EN 50160 [24], which define the acceptable levels of harmonic distortion and the methods used to measure and monitor power quality. These standards typically rely on Fast-Fourier-Transform (FFT)-based approaches due to their simplicity and established use. However, the limitations of FFT, especially in detecting harmonics under non-stationary conditions, create a gap that MUSIC can address.

The integration of MUSIC into existing systems would require modifications in the data processing architecture and compliance with the standards governing power quality reporting:

- **Compliance with Frequency Bins:** Current standards often define specific frequency bins for harmonic reporting. MUSIC, with its high-resolution capability, would need to align its frequency estimation outputs with these bins, ensuring that the results are compatible with existing regulatory frameworks.
- **Dynamic Power Quality Reporting**: Standards focus on steady-state conditions, but modern grids with renewable energy integration experience frequent transients and dynamic behavior. MUSIC's ability to analyze non-stationary signals provides an opportunity to redefine power quality monitoring, expanding the scope of existing standards to include transient harmonics and dynamic conditions.

b) Computational Efficiency and Real-Time Applicability

One of the main considerations when integrating MUSIC into existing power quality monitoring systems is computational efficiency, especially when deployed for real-time monitoring. MUSIC requires the computation of the autocorrelation matrix and its eigenvalue decomposition, which can be computationally intensive, especially for large datasets or high sampling rates required in power quality applications.

To address this, several strategies can be employed:

- **Parallel Computing:** Parallelized implementations of the MUSIC algorithm can be integrated into existing systems to handle real-time data streams, leveraging modern multi-core processors or distributed computing architectures. Techniques such as GPU acceleration and cloud computing platforms could be employed to reduce the computational burden [17].
- **Adaptive Sampling:** In practice, power quality monitoring systems could use adaptive sampling techniques to selectively apply MUSIC only during critical periods, such as when non-stationary behavior is detected, or when harmonic distortion exceeds predefined thresholds [25]. This would optimize system resources by avoiding unnecessary computations during steady-state conditions.
- **Hardware Implementation:** For high-speed, real-time processing, integrating MUSIC into dedicated hardware platforms, such as Field-Programmable Gate Arrays (FPGAs) or Digital Signal Processors (DSPs), would allow for faster execution times and lower latency, making the algorithm more suitable for continuous monitoring [26].

4.2. Limitations of the Synthetic Data Used for the Study

While the synthetic data used in this study provides a controlled environment for evaluating the effectiveness of the MUSIC algorithm, it cannot fully capture the complexities and uncertainties present in real-world power systems. The following are some key limitations associated with using synthetic data [27]:

- **Lack of Environmental Variability:** Real-world power systems are subject to a wide range of environmental factors, such as fluctuating load demands, changing weather conditions, and varying grid configurations. Synthetic data may not fully capture this variability, leading to results that are less representative of actual grid performance.
- **Simplified Noise Models:** In practice, power grids are influenced by a variety of noise sources, including electromagnetic interference, inverter switching noise, and signal degradation from long transmission distances. Synthetic datasets used in this study assume simplified and idealized noise models, which may underestimate the impact of real-world noise on harmonic detection accuracy.
- **Inadequate Representation of Dynamic Grid Conditions:** Synthetic data used in this study models steady-state conditions and controlled transients, which may not reflect the complex, dynamic behavior of power systems with high penetration of renewable energy sources.

5. CONCLUSION

This paper has demonstrated the effectiveness of the MUSIC algorithm for high-resolution harmonic analysis in power systems, particularly in non-stationary and noisy environments. Through simulation results, we have shown that MUSIC offers a more accurate characterization of harmonic components compared to conventional methods like FFT, which typically suffers from limited resolution, particularly in cases with close or weakly separated harmonics. Our results align with and extend previous research, which has acknowledged MUSIC's superior performance in harmonic detection, especially in power systems with renewable energy integration. Comparatively, studies in the literature often reveal FFT's limitations in distinguishing harmonic components under fluctuating conditions, where MUSIC's subspace-based approach excels by accurately isolating harmonics even in complex noise backgrounds. This improved precision, validated through both our simulations and corroborated by other studies, underscores MUSIC's capability as a robust tool for monitoring power quality. Its adoption could lead to more effective and targeted mitigation strategies in modern power systems, providing critical insights into harmonic interactions and supporting the development of grid stability solutions tailored for renewable-rich environments. These results confirm MUSIC's unique contribution to advancing harmonic analysis in dynamic power systems.

. The findings of this study hold significant promise for several application fields, including:

- **Power Quality Monitoring**: Implementing the MUSIC algorithm in real-time power quality monitoring systems can facilitate continuous assessment of harmonic distortion levels, helping utilities to maintain compliance with regulatory standards and minimize equipment damage.
- **Smart Grid Technology**: As smart grid technologies become more prevalent, the integration of advanced harmonic analysis techniques like MUSIC can enhance the overall functionality of these systems by providing real-time insights into power quality, enabling proactive management of harmonic issues.
- **Microgrid Operations**: In microgrid environments, where renewable resources and energy storage systems operate in tandem [28], the MUSIC algorithm can help optimize power quality management, ensuring stability and efficiency in local energy systems.
- **Industrial Applications**: Many industrial facilities are sensitive to power quality issues. The application of the MUSIC algorithm for harmonic analysis can aid industries in identifying and mitigating harmonic sources, improving the performance and lifespan of equipment.
- **Renewable Energy Integration**: The growing penetration of renewables necessitates effective harmonic management to ensure grid stability. The MUSIC algorithm can be employed to assess the impact of distributed energy resources (DERs) on power quality, informing strategies for integrating these resources into existing grids [29].

However, despite its advantages, the MUSIC algorithm faces certain limitations. One of the key challenges is the relationship between the number of harmonics and the degrees of freedom (or the number of sensors used in the system). As the number of harmonics approaches or exceeds the number of available degrees of freedom, the algorithm's ability to resolve and accurately estimate these harmonic components diminishes. This limitation can impact its applicability in systems with a high density of harmonic sources. Furthermore, the computational complexity of MUSIC increases significantly with a higher number of harmonics, as it requires the calculation and decomposition of large covariance matrices. These factors introduce scalability issues when applied to larger power grids or systems with numerous non-linear loads and distributed generators. Moreover, the real-time implementation of the algorithm can be challenging, especially in fast-changing power systems, due to the high computational burden. Optimization techniques, hardware acceleration, or the development of more efficient subspace-based methods will be necessary to overcome these limitations and enable MUSIC's real-time application in large-scale, dynamic power systems.

FUTURE WORK

While this study has primarily relied on simulations and synthetic data to demonstrate the effectiveness of the MUSIC algorithm in harmonic analysis, the next logical step is to validate the results using real-world data from operational power systems. Future work will focus on applying the MUSIC algorithm to harmonic analysis in real power grids, particularly at the Point of Common Coupling (PCC) in systems with high penetration of renewable energy resources.

Several aspects of real-world applicability will be considered, including the validation of harmonic detection in environments with fluctuating power quality due to non-linear loads, inverter-based resources, and intermittent renewable energy generation. Real-world data will allow us to test the robustness of the algorithm against various forms of noise and disturbances that may not be fully captured in synthetic simulations.

Additionally, future work will explore the integration of the MUSIC algorithm into real-time power quality monitoring systems. This will involve addressing the computational challenges discussed in this paper, such as reducing the algorithm's complexity for real-time applications and investigating the potential for hardware acceleration or parallel processing techniques. Furthermore, expanding the analysis to include data preprocessing and a comparison of MUSIC with other high-resolution techniques like ESPRIT and wavelet transform in practical settings will provide deeper insights into the scalability and overall performance of these methods.

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Solomon Mamo Banteywalu: Conceptualization, Formal analysis; investigation; methodology; resources; software; writing—original draft; writing—review & editing. **Tesfaye Hailu Seyoum:** Formal analysis; resources.

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Data available on request from the authors

REFERENCES

[1]. Bollen, M. H., & Hassan, F. (2011). Integration of distributed generation in the power system. John Wiley & Sons. DOI:10.1002/9781118029039

[2]. Blaabjerg, F., Teodorescu, R., Liserre, M., & Timbus, A. V. (2019). Overview of control and grid synchronization for distributed power generation systems. IEEE Transactions on Industrial Electronics, 53(5), 1398–1409, DOI: 10.1109/TIE.2006.881997

[3]. Venkatesan, R., Kumar, C., Balamurugan, C. R., & Senjyu, T. (2024). Enhancing power quality in grid-connected hybrid renewable energy systems using UPQC and

optimized O-FOPID. Frontiers in Energy Research, 12, 1425412. DOI:10.3389/fenrg.2024.1425412

[4]. El-Bahay, M.H., Lotfy, M.E. & El-Hameed, M.A. Computational Methods to Mitigate the Effect of High Penetration of Renewable Energy Sources on Power System Frequency Regulation: A Comprehensive Review. Arch Computat Methods Eng 30, 703–726 (2023). DOI:10.1007/s11831-022-09813-9

[5]. Francisco, C. D. L. R. (2017). Harmonics, power systems, and smart grids. CRC press. DOI:10.1201/9781315215174

[6]. Schmidt, R. (1986). Multiple emitter location and signal parameter estimation. IEEE Transactions on Antennas and Propagation, 34(3), 276-280. DOI: 10.1109/TAP.1986.1143830.

[7]. Shahnaz, C., Sharif, M. S. E., Hoque, M. Z., & Islam, M. S. (2016). Analysis of High Resolution Spectral Methods to Assess Power Quality. European Journal of Advances in Engineering and Technology, 3(12), 7-15. DOI:10.1109/TIM.2005.862015

[8]. Li, T., & Tang, Y. (2010, September). Frequency estimation based on modulation FFT and MUSIC algorithm. In 2010 First International Conference on Pervasive Computing, Signal Processing and Applications (pp. 525-528). IEEE. DOI:10.1109/PCSPA.2010.132

[9]. De Cheveigné, A., & Kawahara, H. (2002). YIN, a fundamental frequency estimator for speech and music. The Journal of the Acoustical Society of America, 111(4), 1917-1930. DOI https://doi.org/10.1121/1.1458024

[10]. Rhif M, Ben Abbes A, Farah IR, Martínez B, Sang Y. Wavelet Transform Application for/in Non-Stationary Time-Series Analysis: A Review. *Applied Sciences*. 2019; 9(7):1345. DOI: 10.3390/app9071345

[11]. Zeng, W. J., So, H. C., & Huang, L. (2013). $\ell _ {p} $-MUSIC: Robust Direction-of-Arrival Estimator for Impulsive Noise Environments. IEEE Transactions on Signal Processing, 61(17), 4296-4308. DOI:10.1109/TSP.2013.2263502 :

[12]. M. Haardt, F. Roemer and G. Del Galdo, "Higher-Order SVD-Based Subspace Estimation to Improve the Parameter Estimation Accuracy in Multidimensional Harmonic Retrieval Problems," in IEEE Transactions on Signal Processing, vol. 56, no. 7, pp. 3198-3213, July 2008, DOI: 10.1109/TSP.2008.917929

[13]. M. Albu, P. Postolache and C. Golovanov, "Non-stationary signals' analysis in power systems. A time-frequency approach," *2000 10th Mediterranean Electrotechnical Conference. Information Technology and Electrotechnology for the Mediterranean Countries. Proceedings. MeleCon 2000 (Cat. No.00CH37099)*, Lemesos, Cyprus, 2000, pp. 1181-1184 vol.3, DOI: 10.1109/MELCON.2000.879746

[14]. P. Janik and Z. Waclawek, "MUSIC algorithm for estimation of parameters of signals in power system," 2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC), Rome, Italy, 2015, pp. 2236-2240, DOI: 10.1109/EEEIC.2015.7165530

[15]. O. Ceaki, G. Seritan, R. Vatu and M. Mancasi, "Analysis of power quality improvement in smart grids," 2017 10th International Symposium on Advanced Topics in Electrical Engineering (ATEE), Bucharest, Romania, 2017, pp. 797-801. DOI: 10.1109/ATEE.2017.7905104

[16]. Tareen WUK, Aamir M, Mekhilef S, Nakaoka M, Seyedmahmoudian M, Horan B, Memon MA, Baig NA. Mitigation of Power Quality Issues Due to High Penetration of Renewable Energy Sources in Electric Grid Systems Using Three-Phase APF/STATCOM Technologies: A Review. Energies. 2018; 11(6):1491. 10.3390/en11061491

[17]. Q. Huang and N. Lu, "Optimized Real-Time MUSIC Algorithm With CPU-GPU Architecture," in IEEE Access, vol. 9, pp. 54067-54077, 2021, DOI :10.1109/ACCESS.2021.3070980

[18]. IEEE Standard for Harmonic Control in Electric Power Systems," in *IEEE Std 519-2022 (Revision of IEEE Std 519-2014)*, vol., no., pp.1-31, 5 Aug. 2022, DOI: 10.1109/IEEESTD.2022.9848440

[19]. A.V. Oppenheim and R.W. Schafer, "Discrete-Time Signal Processing," 3rd Edition, Prentice Hall, 2010. ISBN : 9780131988422

[20]. K. K. Sahu and R. D. Gupta, "Characterization of Noise in Wireless Communication Systems," Journal of Communications and Networks, vol. 24, no. 2, pp. 126-135, 2022. DOI:10.1063/1.4871682

[21]. Ikeguchi, T., & Aihara, K. (1997). Difference correlation can distinguish deterministic chaos from 1/f α-type colored noise. Physical Review E, 55(3), 2530. DOI: 10.1103/PhysRevE.55.2530

[22]. A. K. Jain, M. D. Kottapalli, and K. S. K. Bhanu, "Impulsive Noise Detection and Mitigation Techniques in Wireless Communication Systems," Wireless Communications and Mobile Computing, vol. 2022, 2022. DOI:10.1109/ICECE.2012.6471543

[23]. Dalali, M., & Jalilian, A. (2015). Indices for measurement of harmonic distortion in power systems according to IEC 61000-4-7 standard. IET Generation, Transmission & Distribution, 9(14), 1903-1912. DOI:10.1049/iet-gtd.2015.0366

[24]. Start, D. J. (1995, November). A review of the new CENELEC standard EN 50160. In IEE Colloquium on Issues in Power Quality (pp. 4-1). IET. DOI:10.1049/ic:19951422

[25]. Liu, K., Mei, Y., & Shi, J. (2015). An adaptive sampling strategy for online high-dimensional process monitoring. Technometrics, 57(3), 305-319. DOI:10.1080/00401706.2014.947005

[26]. Ruiz-Rosero, J., Ramirez-Gonzalez, G., & Khanna, R. (2019). Field programmable gate array applications—A scientometric review. Computation, 7(4), 63. DOI:10.3390/computation7040063

[27]. Donoho, D. L., Maleki, A., Rahman, I. U., Shahram, M., & Stodden, V. (2008). Reproducible research in computational harmonic analysis. Computing in Science & Engineering, 11(1), 8-18. DOI:10.1109/MCSE.2009.15

[28]. Nazir, M. S., Abdalla, A. N., Wang, Y., Chu, Z., Jie, J., Tian, P., ... & Tang, Y. (2020). Optimization configuration of energy storage capacity based on the microgrid reliable output power. Journal of Energy Storage, 32, 101866. DOI:10.1016/j.est.2020.101866

[29]. Dashtdar, M., Nazir, M. S., Hosseinimoghadam, S. M. S., Bajaj, M., & Goud B, S. (2022). Improving the sharing of active and reactive power of the islanded microgrid based on load voltage control. Smart Science, 10(2), 142-157. DOI:10.1080/23080477.2021.2012010