DETECTION OF ONSET OF DISTURBANCE FOR INERTIA ESTIMATION USING MACHINE LEARNING

A Project Report Submitted

by

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THESIS CERTIFICATE

This is to certify that the thesis titled **DETECTION OF ONSET OF DISTURBANCE FOR INERTIA ESTIMATION USING MACHINE LEARNING**, submitted by **Aditya Kumar**, to the Indian Institute of Technology, Patna, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

This project focuses on the detection of disturbances in a 2-area power system for estimating inertia using machine learning techniques. The project investigates an old paper that uses a fixed threshold detection method to isolate the inertial response from the overall frequency response and introduces a new method for the same. The data collection phase involved simulating a transfer function model of a 2-area system and collecting data on disturbance signals, center of inertia frequency, and disturbance magnitude from 19 signals, each with 2000 samples. The project till now has explored the use of the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm for disturbance detection.

Future work includes the calculation and optimization of hyper-parameters for the DBSCAN algorithm, training the model to accurately determine the onset of disturbances, and exploring other machine learning models such as HDBSCAN and OPTICS. Plans also include adding more features to the dataset to enhance the accuracy of the model's predictions.

CHAPTER 1

INTRODUCTION

The stability and reliability of power systems are crucial for ensuring uninterrupted electricity supply to consumers. Disturbances in power systems, such as sudden load changes or faults, can lead to disruptions in power supply and have severe consequences. Early detection and classification of disturbances are essential for maintaining the stability of power systems.

This project focuses on the detection of disturbances in a 2-area power system for estimating inertia using machine learning techniques. It builds upon an old paper that used a fixed threshold detection method to isolate the inertial response from the overall frequency response. The project introduces a new method for disturbance detection and investigates the use of the **Density-Based Spatial Clustering of Applications with Noise (DBSCAN)** algorithm for this purpose.

The data collection phase involved simulating a transfer function model of a 2-area system and collecting data on disturbance signals, center of inertia frequency, and disturbance magnitude from 19 signals, each with 2000 samples. The project has explored the initial implementation of the DBSCAN algorithm for disturbance detection. Future work includes the calculation and optimization of hyper-parameters for the DBSCAN algorithm, training the model to accurately determine the onset of disturbances, and exploring other machine learning models such as **HDBSCAN** and **OPTICS**. Additionally, plans include adding more features to the dataset to enhance the accuracy of the model's predictions.

1.1 Inertia in power systems

In power systems, the inertia of machines, like generators and turbines, is crucial for stability. It refers to the energy stored in large rotating generators and some industrial motors, which gives them the tendency to remain rotating. This property helps stabilize the system's frequency, buffering against sudden demand or supply changes. When large loads connect or disconnect suddenly, machine inertia absorbs the impact, allowing the system to stabilize.

Moreover, inertia aids the system's response to disturbances. It stores kinetic energy, helping the system ride through disruptions. This acts as a "shock absorber," preventing widespread failures. Overall, machine inertia is vital for grid stability, ensuring reliable operation. Managing and understanding inertia is key to efficient power system operation.

In conclusion, machine inertia is vital for power system stability. It helps maintain frequency during load changes and aids in the system's response to disturbances. Managing inertia is crucial for a reliable power supply.

1.2 Centre of Inertia Frequency

The center of inertia frequency (COI frequency) is a crucial parameter in power systems, reflecting the balance between generation and demand. It represents the weighted average frequency of synchronous generators in the grid, indicating system stability. Fluctuations in COI frequency suggest imbalances in generation and load, potentially leading to instability and blackouts. Monitoring and controlling COI frequency are vital for grid stability, helping operators make real-time adjustments to maintain system balance.

COI frequency is influenced by factors like generation-load balance, control system responses, and disturbances. Deviations from the nominal frequency signal cause imbalances, prompting corrective actions. Operators rely on COI frequency to assess grid health and manage generation-load balance for stability. It's also used in control and protection schemes to mitigate disturbances and prevent widespread outages.

In conclusion, the center of inertia frequency is pivotal for grid stability and reliability. It serves as a critical indicator of system health, guiding operators in maintaining balance and mitigating disruptions. Understanding and controlling COI frequency are essential for ensuring the efficient and reliable operation of power systems.

$$\text{COI frequency} = \frac{\sum_{i=1}^{n} f_i \cdot H_i}{\sum_{i=1}^{n} H_i}$$

In the above formula, H_i is the inertia constant of the ith generator, expressed at a common VA base. f_i is filtered individual frequency measurements.

1.3 The Swing equation

The swing equation is a critical component of power system analysis, providing insight into the dynamic behavior of synchronous generators within a multi-machine system. It describes the electromechanical interaction between the mechanical and electrical components of a generator, offering a fundamental understanding of power system stability.

The swing equation is represented by the formula:

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

where:

H_sys: system inertia constant, reflecting the ability of the system to store and release energy.

S: nominal apparent power of the system.

f: measured frequency

f_0: nominal system frequency.

P_m: is the mechanical power input to the generator.

P_e: is the electrical power output of the generator.

This equation illustrates how changes in mechanical power input and electrical power output affect the system frequency, offering valuable insights into the stability of the power system. The conventional swing equation-based method of inertia estimation that calculates the value of inertia constant by observing the frequency response for a known disturbance is widely used for power system studies [1].

CHAPTER 2

THE OLD METHOD: FIXED THRESHOLD DETECTION METHOD

In [2], One of the essential steps to carry out curve fitting of the measured frequency response is to identify the time of onset of the disturbance. For this study, a RoCoF threshold of 0.05 Hz/s was used to identify the exact starting time of the event. A moving average filter of 50 ms was applied to the measured RoCoF value to minimize the effect of measurement errors or noise. Any sample exceeding this threshold value was considered a disturbance.

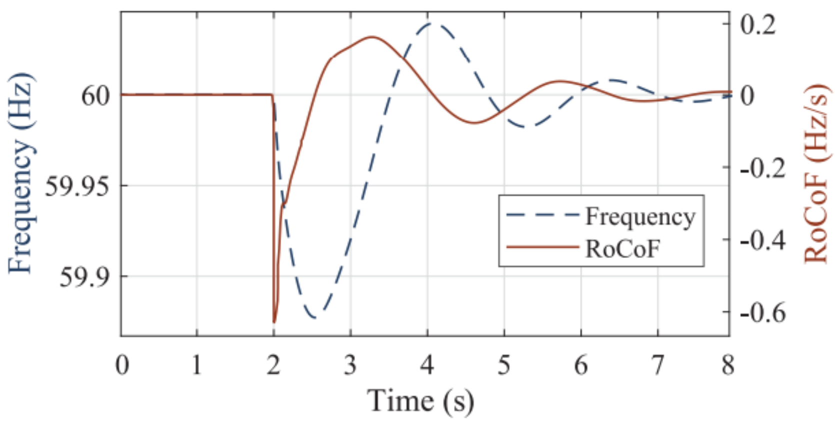

Figure 2.1: Frequency and RoCoF vs time [2]

This method has many disadvantages:

1. It requires careful selection of the threshold and window length, which can be challenging and system-dependent.
2. Inaccurate for small disturbances that may not exceed the threshold.
3. Very susceptible to phasor measurement unit (PMU) noise.
4. The method is not reliable for low-inertia power systems.

CHAPTER 3

DATA COLLECTION FOR OUR MACHINE LEARNING APPROACH

The data collection process for this project involved simulating a transfer function model of a two-area power system and generating synthetic data to mimic real-world scenarios. The system was modeled using mathematical equations and simulation software to replicate the behavior of generators, loads, and transmission lines. The simulation was designed to introduce step disturbances of varying magnitudes to the system, simulating different levels of faults or disturbances that could occur in an actual power system.

For each simulation run, data was collected on the disturbance signal, center of inertia frequency, and disturbance magnitude. The disturbance signal represents the deviation in frequency caused by the disturbance, while the center of inertia frequency is a key parameter that reflects the overall balance between generation and demand in the system. The disturbance magnitude indicates the severity of the disturbance, with larger magnitudes corresponding to more significant faults or disturbances.

The data collection process resulted in a dataset consisting of **19** signals, each containing **2000** samples. Each signal corresponds to a different disturbance magnitude, ranging from 0.1 to 1 unit, providing a comprehensive range of data to train and test the machine learning models. This dataset serves as the foundation for the project, allowing us to analyze the performance of different machine learning algorithms in detecting and estimating the onset of disturbances in a 2-area power system.

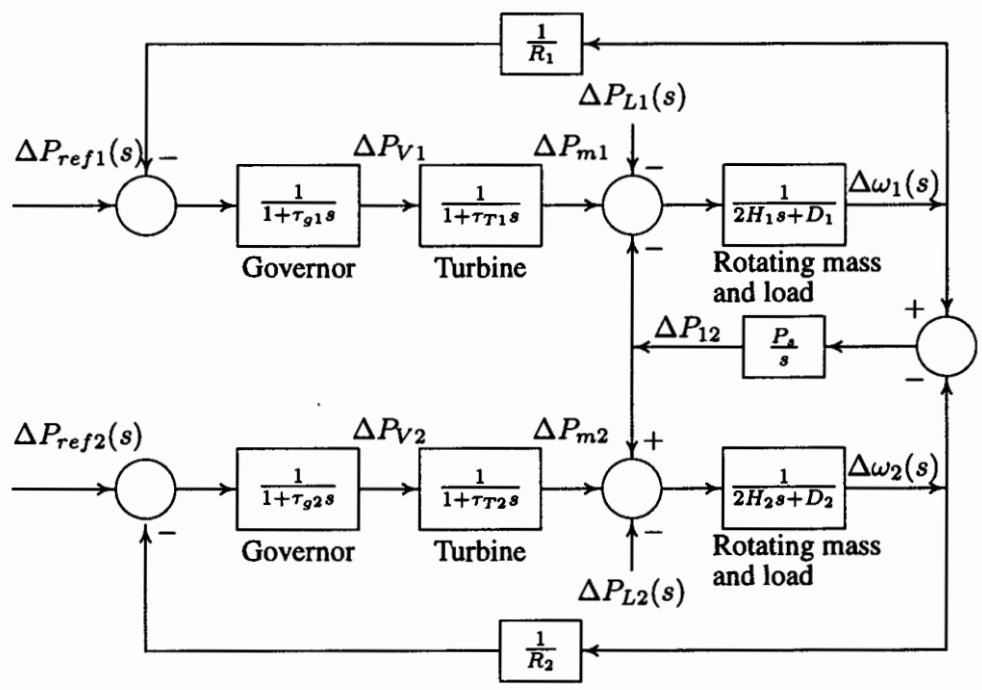

Figure 3.1: Transfer function model of a two area system

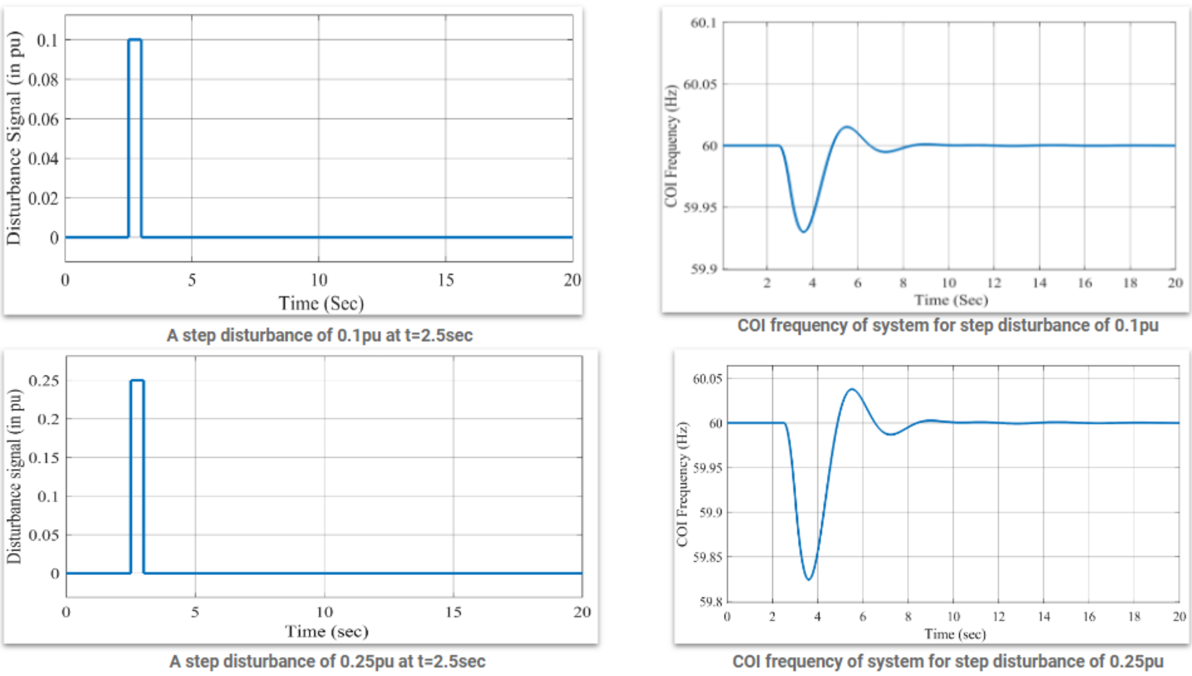

Figure 3.2: Step disturbances and corresponding COI Frequency vs time graphs

CHAPTER 4

DENSITY-BASED SPATIAL CLUSTERING OF APPLICATIONS WITH NOISE (DBSCAN)

After exploring several clustering algorithms like K-means clustering and the Gaussian Mixture Model (GMM), we decided to go with Density Based Spatial Clustering of Applications with Noise (DBSCAN).

4.1 Introduction

DBSCAN is a density based clustering algorithm proposed by Martin Ester, Hans-Peter Kriegel, Jörg Sander and Xiaowei Xu [3]. It is a density-based clustering algorithm: given a set of points in some space, it groups together points that are closely packed together, marking as outliers points that lie alone in low-density regions.

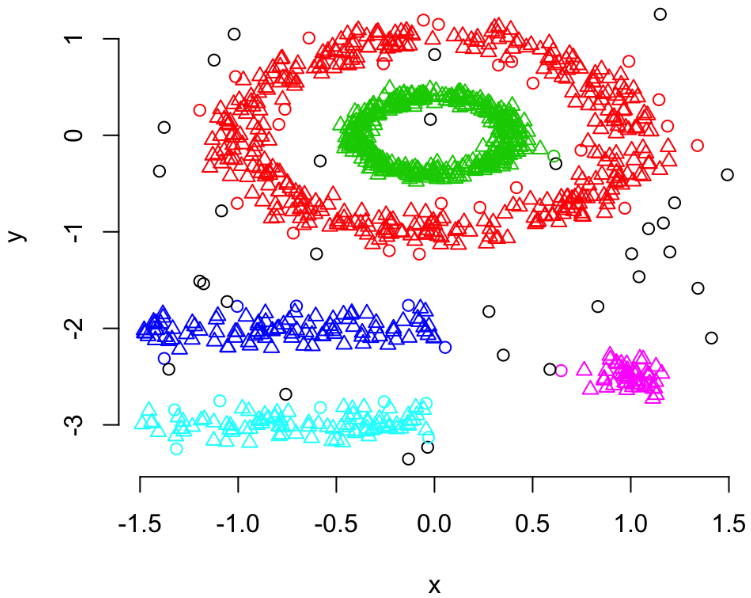

Figure 4.1: Density Based Spatial Clustering Of Applications with Noise (DBSCAN)

It does this by defining two key hyper-parameters:

1. **epsilon (ε):** This parameter defines the maximum distance between two points to be considered neighbors.

2. **minpts (minimum points):** This parameter defines the minimum number of points required within the ε-neighborhood of a point to consider it a core point.

For the purpose of DBSCAN clustering, based on hyper-parameters, the points are classified as core points, border points and noise (outliers), as follows:

1. **Core Points:** These are points that have at least a minimum number of points (minPts) within a specific radius (ε) of them. These points are considered to be dense areas and form the core of the clusters.
2. **Border Points:** These are points that are reachable from a core point but have fewer than minPts points within their ε-neighborhood. They lie on the edges of the clusters.
3. **Noise (Outliers):** These are points that are not core points and are not reachable from any core point. They are considered to be outliers or isolated points.

In the figure below, red points represent core points, yellow points represent border points, and blue points represent noise.

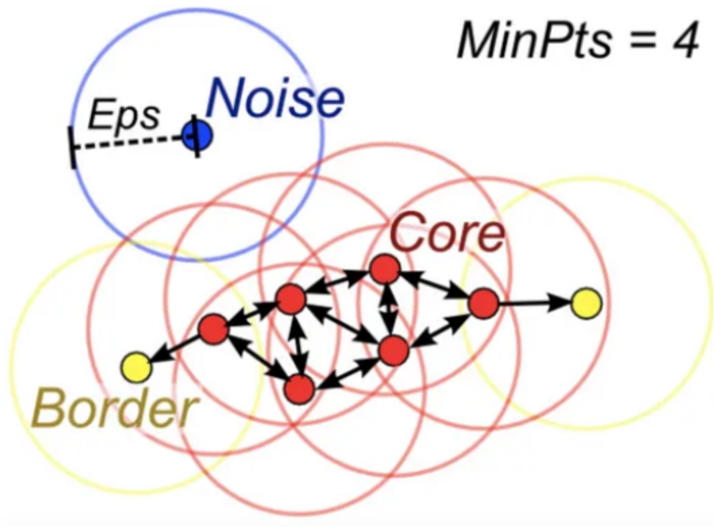

Figure 4.2: Segregation of points based on hyper-parameters of DBSCAN

4.2 How it will help in detecting the onset of disturbance?

1. **Density Estimation:** DBSCAN calculates the distance between each data point and its neighboring points. If the distance is less than a specified threshold (epsilon), the point is considered part of a cluster.

2. **Cluster Formation:** Points that are within epsilon distance of each other are grouped into the same cluster. This helps in identifying areas in the dataset where disturbances occur, as these areas will have points that are close to each other due to the similar nature of disturbances.

3. **Outlier Detection:** Points that are not within epsilon distance of any other point are considered outliers. These outliers represent data points that do not fit into any cluster and are potentially indicative of disturbances in the system.

4. **Pinpointing Disturbance Time:** By identifying clusters associated with deviations, it essentially isolates the time period when those deviations occurred, helping to pinpoint the exact time of a disturbance within the data.

Unlike traditional clustering algorithms such as K-means, DBSCAN does not require the user to specify the number of clusters beforehand, making it particularly useful for datasets where the number of clusters is not known a priori. It has the ability to identify clusters of arbitrary shapes and sizes. It is also robust to noise and can handle datasets with varying densities.

Overall, DBSCAN is a powerful clustering algorithm that is widely used in various applications due to its flexibility and effectiveness.

CHAPTER 5

Conclusion and Future Works

The data collection phase of this project involved collecting simulated data from a two-area system consisting of 19 signals with 2000 samples each. This dataset includes disturbance signals, center of inertia frequency, and disturbance magnitude. Moving forward, we explored the use of the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm for disturbance detection in power systems.

In the future, we plan to further refine our model by calculating and optimizing the hyper-parameters involved in the DBSCAN algorithm. This will help improve the accuracy and efficiency of our disturbance detection system. Additionally, we aim to implement the DBSCAN algorithm for the detection of the onset of disturbances in power systems. Furthermore, we plan to explore and implement other clustering algorithms, such as Hierarchical DBSCAN (HDBSCAN) and Ordering Points To Identify the Clustering Structure (OPTICS), to compare their performance with DBSCAN. Finally, we plan to expand our dataset with additional features to enhance the performance of our model and improve its ability to accurately detect disturbances in power systems.

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